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Mecanismos y Técnicas avanzadas para la Localización con multi-tecnología

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He aquí mi secreto, que no puede ser más simple: sólo con el corazón se puede ver bien; lo esencial es invisible a los ojos.

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Contenidos

Abstract

Society is currently undergoing a digital revolution in which Internet-based services offered to the user are increasingly personalized. Users are always connected, with services that have increasing requirements in bandwidth, latency and reliability. Thanks to cellular networks, mobility is also on the rise, with services that are not only personalized to the users' taste, needs and characteristics, but also to their location. Around this concept, the fifth generation of cell phones (5G) is postulated as a technology that will enable many services thanks to its low latency, high bandwidths and precise positioning. Originally, 5G network-based location was anticipated to have centimeter-level precision. However, initial estimates have since been revised, and accuracy is now expected to be within several meters. Since there is still no de-facto technology for indoor positioning as is the case with outdoor satellite technology, different technologies have been thoroughly investigated during the development of this thesis. Awaiting the implementation for 5G of time-based protocols in order to achieve more accurate localization, the two most promising technologies at the present time are Ultra Wide Band (UWB) technology and WiFi with the IEEE 802.11mc protocol that can be used as a placeholder for 5G as a precise location provider. Both technologies use timestamps and protocols that exchange multiple messages to accurately estimate the distance to the user. However, having seen the potential of the different technologies, the study of joint use has been carried out to see the advantages that can be obtained. In addition, to improve accuracy, range and reduce deployment costs, it can also be seen that these technologies can be combined with other technologies or with different sensors.

In our pursuit of the development of algorithms to combine the different 4G/5G, UWB or WiFi technologies, we have sought to study different location-based applications and their respective requirements. Given that centimeter-precise outdoor positioning has already been successfully accomplished, with technologies such as Real Time Kinematics (RTK), we aim

at achieving similar precisions in indoors scenarios, where the conditions are challenging for signal propagation. Our proposed fusion technique and the characterization of the technologies have been carried out in complex scenarios such as indoor, construction or emergency scenarios since they are very dynamic scenarios with many elements that produce reflections and signal blockages that end up affecting the location precision.

In order to fulfil the objectives of the thesis, this study has focused on developing prototypes and services that benefit from the fusion of technologies. By leveraging the different integrated sensors within a smartphone, we have successfully developed an application and platform capable of simultaneously accessing location data from multiple sources and employing diverse location algorithms. These innovations have supported the research of several projects exploring different localization techniques based on multiple technologies.

Finally, a unified architecture to validate localization algorithms for technologies that have not yet been released to the market has been proposed. With the implementation of this architecture, early progress can be made in the development and research of future mobile network technologies, such as 6G, and novel services based on localization.

Resumen

La sociedad vive actualmente una revolución digital en la que los servicios basados en Internet que se ofrecen al usuario son cada vez más personalizados. Los usuarios están siempre conectados, con servicios cada vez más exigentes en ancho de banda, latencia y fiabilidad. Gracias a las redes celulares, la movilidad también va en aumento, con servicios que no sólo se personalizan en función de los gustos, necesidades y características de los usuarios, sino también de su ubicación. En torno a este concepto, la quinta generación de telefonía móvil (5G) se postula como una tecnología que permitirá numerosos servicios gracias a su baja latencia, sus grandes anchos de banda y su posicionamiento preciso. En un principio, se preveía que la localización basada en la red 5G tendría una precisión de centímetros. Sin embargo, las estimaciones iniciales se han revisado y ahora se espera una precisión de varios metros. Dado que aún no existe una tecnología de facto para el posicionamiento en interiores como ocurre con la tecnología satelital en exteriores, durante el desarrollo de esta tesis se han investigado a fondo diferentes tecnologías. A la espera de la implementación en 5G de protocolos basados en el tiempo para lograr una localización más precisa, las dos tecnologías más prometedoras en la actualidad son la tecnología de banda ultra ancha (UWB) y WiFi con el protocolo IEEE 802.11mc que pueden utilizarse como sustituto del 5G como proveedor de localización precisa. Ambas tecnologías utilizan marcas temporales y protocolos que intercambian múltiples mensajes para estimar con precisión la distancia al usuario. Sin embargo, visto el potencial de las distintas tecnologías, se ha estudiado su uso conjunto para ver las ventajas que se pueden obtener. Además, para mejorar la precisión, el alcance y reducir los costes de despliegue, también se ha visto que estas tecnologías pueden combinarse con otras o con distintos sensores.

En nuestro afán por desarrollar algoritmos que combinen las distintas tecnologías 4G/5G, UWB o WiFi, hemos tratado de estudiar distintas aplicaciones basadas en la localización y sus respectivos requisitos. Dado que ya

se ha logrado con éxito el posicionamiento con precisión de centímetros en exteriores, con tecnologías como la navegación cinética satelital en tiempo real (RTK), nuestro objetivo es alcanzar precisiones similares en escenarios interiores, nuestro objetivo es alcanzar precisiones similares en escenarios interiores, donde las condiciones son complicadas para la propagación de la señal. Nuestra técnica de fusión propuesta y la caracterización de las tecnologías se han llevado a cabo en escenarios complejos como interiores, de construcción o de emergencia ya que son escenarios muy dinámicos con muchos elementos que producen reflexiones y bloqueos de señal que acaban afectando a la precisión de la localización.

Para cumplir los objetivos de la tesis, este estudio se ha centrado en desarrollar prototipos y servicios que se beneficien de la fusión de tecnologías. Mediante los diferentes sensores integrados en un smartphone, hemos desarrollado con éxito una aplicación y una plataforma capaces de acceder simultáneamente a datos de localización de múltiples fuentes y emplear diversos algoritmos de localización. Estas innovaciones han apoyado la investigación de varios proyectos que exploran diferentes técnicas de localización basadas en múltiples tecnologías.

Por último, se ha propuesto una arquitectura unificada para validar algoritmos de localización para tecnologías que aún no han salido al mercado. Con la implantación de esta arquitectura se podrá avanzar pronto en el desarrollo y la investigación de futuras tecnologías de redes móviles, como la 6G, y novedosos servicios basados en la localización.

Lista de Acrónimos

3GPP	3rd Generation Partnership Project
Adaboost	*Adapting Boosting*
AoA	*Angle of Arrival*
IA	Inteligencia Artificial
AoD	*Angle of Departure*
AP	*Access Point*
B5G	*Beyond 5G*
BLE	*Bluetooth Low Energy*
CDF	*Cumulative Density Function*
CID	*Cell IDentification*
DTA	*Decision Tree Adaboost*
DTR	*Decision Tree Regressor*
EKF	*Extended Kalman Filter*
FCC	*Federal Communications Commission*
FTM	*Fine Time Measurement*
FR	*Frequency Range*
GLONASS	*GLObal NAvigation Satellite System*
GNSS	*Global Navigation Satellite System*

GPS	*Global Positioning System*
GSM	*Global System for Mobile Communications*
IoT	*Internet of Things*
I+D	Investigación y Desarrollo
LaaS	*Localization-as-a-Service*
LoS	*Line of Sight*
LPP	*LTE Positioning Protocol*
LS	*Least Square*
LTA	*Linear Tree Adaboost*
LTE	*Long Term Evolution*
LTE-A	*LTE-Advanced*
MIMO	*Multiple Input Multiple Output*
ML	*Machine Learning*
NLoS	*Non Line of Sight*
NRPPa	*New Radio Positioning Protocol A*
Open RAN	Open Radio Access Network
PAN	*Personal Area Network*
PNT	Posición, Navegación y Tiempo
RAN	*Radio Access Network*
RF	*Random Forest*
RSSI	*Received Signal Strength Indicator*
RTK	*Real-Time Kinematic*
RTT	*Round Trip Time*
TDoA	*Time Difference of Arrival*

ToF *Time of Flight*

UE *User Equipment*

UWB *Ultra Wide-Band*

WLS *Weighted Least Square*

WL *Weak Learner*

XR *eXtended Reality*

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Capítulo 1

Introducción

Este capítulo ofrece una introducción al trabajo realizado durante esta tesis. En la Sección 1.1 se presenta la motivación de este trabajo, indicando cómo la localización es un servicio fundamental para el futuro de las aplicaciones. A continuación, se presentan los objetivos perseguidos en esta tesis en la Sección 1.3. Por último, se describe la estructura del documento en la Sección 1.4.

1.1 Motivación

La localización consiste en determinar la posición de un objetivo con respecto a un marco de coordenadas de referencia. Los sistemas de localización han constituido un reto para la humanidad desde el principio de los tiempos, resuelto en primera instancia utilizando las estrellas y otros cuerpos celestes como guía. Hoy en día, los sistemas mundiales de navegación por satélite *Global Navigation Satellite System* (GNSS) se han convertido en la columna vertebral y el principal proveedor de información Posición, Navegación y Tiempo (PNT). Las futuras aplicaciones de los sistemas de transporte inteligentes, como los coches autónomos o la completa integración de robots en las industrias, dependen del posicionamiento absoluto y preciso para garantizar una navegación segura que ya es una necesidad [1] y que se basará no solo en GNSS sino en otras tecnologías como 5G/6G [2], WiFi [3] o tecnologías de *Ultra Wide-Band* (UWB) [4].

Existe una dependencia cada vez mayor de la tecnología satelital para fines de cronometraje o localización en escenarios donde ninguna otra tecnología es capaz de dar servicio, como los océanos o desiertos. Por ello, y gracias a una precisión cada vez mejor, podemos afirmar que GNSS se ha impuesto de forma absoluta para el posicionamiento en zonas de exterior. La tecnología GNSS ha experimentado un importante desarrollo en los últimos años, especialmente con el despliegue de las constelaciones satelitales europea (Galileo) y china (BeiDou), y la modernización del americano (*Global Positioning System* (GPS)) y del ruso (*GLObal NAvigation Satellite System* (GLONASS)). Mediante el uso de GNSS en receptores de uso común obtenemos una precisión del orden de pocos metros [5]. Existen algunas técnicas como *Real-Time Kinematic* (RTK) que permiten localizar al usuario de forma precisa e instantánea. Sin embargo, este método es viable únicamente para entornos abiertos, es decir, espacios dónde la visión hacia el cielo es posible sin grandes bloqueos. Es por ello que para zonas de interior, donde nos encontramos con obstáculos principalmente como paredes o techos, el error para el posicionar al usuario aumenta considerablemente y nos impide conocer la localización de éste de forma precisa. Es por ello que otras tecnologías buscan imponerse en el mercado como la tecnología de-facto para este tipo de escenarios.

A lo largo de los años, se ha podido observar un evidente progreso tecnológico en las redes de telecomunicaciones, especialmente en las redes móviles. A principios de los años 90, la primera red de telefonía celular digital (*Global System for Mobile Communications* (GSM)) fue instalada con un gran éxito comercial en el mundo [6]. Para esta tecnología, los requisitos exigidos por la red eran tremendamente inferiores a los actuales. Con el paso de los años, la tecnología ha mejorado proveyendo al usuario de unas ciertas capacidades nuevas, como el acceso a internet para la descarga de archivos más pesados o el uso continuo de la red celular para usuarios que se desplazan con alta velocidad, entre otros servicios. No obstante, con la aparición del 5G, que ya es una realidad, se requieren unas características cada vez más complejas, incluyendo una latencia reducida en el rango de milisegundos o un posicionamiento del usuario en tiempo real y con una precisión muy alta, en el orden de los centímetros.

Aunque la red celular ha mejorado con el tiempo, no es la única tecnología que ha ido evolucionando. Durante años, tecnologías como Bluetooth [7], UWB [8] y WiFi [9] han mejorado y refinado sus protocolos para ofrecer al usuario una amplia gama de servicios, al igual que la red celular. Mediante el uso de estas tecnologías, se logra una localización precisa del usuario en interiores, aunque cada una de ellas posee limitaciones y distintos niveles de precisión. Por otro lado, se ha anunciado por parte del 3rd Generation Partnership Project (3GPP) que la nueva generación 5G podrá localizar a los usuarios de manera precisa en entornos tanto interiores como exteriores [10]. Sin embargo, como su implementación aún es parcial, no se ha podido verificar el cumplimiento de este requisito hasta el momento.

Debido a que los requisitos de los servicios basados en localización son cada vez más elevados, el propósito de este trabajo consiste en fusionar las tecnologías más utilizadas, o con mejor proyección, en entornos de interior con diferentes técnicas con el fin de mejorar los servicios de red asociados a la localización que se le puede brindar a un usuario final. En esta tesis se ha explorado cómo aprovechar la información disponible de diversas fuentes de manera oportunista para mejorar la precisión del servicio de localización, todo dentro de un marco común. El objetivo final es brindar a los usuarios una experiencia de localización más precisa y en tiempo real, lo que permitiría ampliar las opciones y personalización de los servicios que se les ofrecen, a la vez que se gestiona de manera más eficiente los recursos disponibles.

1.2 Preliminares

Esta tesis se ha realizado en el Grupo de Mobile Networks (MOBILENET) de la Universidad de Málaga, perteneciente al Instituto Universitario de Investigación en Telecomunicación (TELMA). Este equipo de investigación se dedica a la mejora de las redes de telecomunicaciones móviles actuales y al diseño de las futuras, especialmente mediante el desarrollo de novedosas técnicas, como *zero-touch networks* [11]. El grupo MOBILENET se originó en el año 2000 en una colaboración del Grupo de Ingeniería de Comunicaciones (GIC) con Nokia Networks para crear un Centro de Investigación en Comunicaciones Móviles, establecido en el Parque Tecnológico de Andalucía (PTA) en Málaga, cuyo personal incluía personal experimentado de Nokia, así como más de 50 empleados y profesores del GIC. Uno de los proyectos de partida de esta colaboración consistió en el desarrollo de una herramienta de resolución automática de problemas en *Radio Access Network* (RAN), que sentó algunas de las bases para la incorporación de datos reales de redes celulares y la experiencia de ingenieros en sistemas de resolución automática de problemas.

Desde el inicio de su actividad, el grupo MOBILENET ha participado en proyectos de desarrollo de técnica de gestión automática de red basada en Inteligencia Artificial (IA) en consorcios con empresas nacionales e internacionales. Algunos de los más representativos son el proyecto EUREKA CELTIC "GANDALF: Monitorización y autoajuste de parámetros RRM en una red multisistema" (2005-2008) y MONOLOC (2011-2014). Durante el transcurso de estos proyectos, se desarrolló un simulador *Long*

Term Evolution (LTE) a nivel de sistema que se fue mejorando sucesivamente para incluir capacidades de localización.

Una parte sustancial del desarrollo de esta tesis se ha enmarcado parcialmente en el proyecto europeo H2020 LOCUS [12] (LOCalization and analytics on-demand embedded in the 5G ecosystem, for Ubiquitous vertical applicationS) con especial atención a la localización de usuarios basadas en tecnologías dentro y fuera del 3GPP y la gestión inteligente de redes. Además, el estudio realizado en este proyecto se ha podido trasladar a otros proyectos para la localización de operarios en zonas de construcción dentro del proyecto TEDES-5G [13], a la localización de víctimas en escenarios de emergencia en el marco del proyecto PENTA [14] o el uso de localización para mejorar el sistema educativo dentro del proyecto MAORI [15].

1.3 Desafíos y objetivos

El principal objetivo de esta tesis consiste en mejorar el rendimiento de los sistemas de localización basados en la red móvil en escenarios con condiciones de propagación complejas mediante el uso de diferentes tecnologías radio de forma simultánea, como la red celular, WiFi o UWB, en diferentes escenarios como interiores, zonas de construcción o emergencias. Es por ello que en este trabajo se abordan varios desafíos a los que se enfrenta. El primero de ellos (Des. 1) consiste en mejorar la localización del usuario antes de aplicar filtros para la navegación como el filtro de Kalman [16] o el de partículas [17]. Para esto, se utilizará la información del entorno de las diferentes tecnologías disponibles en un instante de tiempo específico, es decir, en el momento previo al uso de los filtros. Para lograr esto, es necesario desarrollar un sistema para la recopilación y procesamiento de medidas en tiempo real o diferido (Des. 2), lo que nos permitirá analizar y caracterizar los algoritmos y tecnologías propuestas estudiadas a lo largo de esta tesis (Des. 3). Una vez que hayamos estudiado las distintas tecnologías, será necesario comprobar la aplicabilidad directa y sencilla de la localización precisa con multitecnología en el mundo real. Por lo tanto, se han desarrollado algunos conceptos para aplicaciones basadas en la localización en el mundo real (Des. 4), como la localización y detección de víctimas en escenarios de emergencia, el posicionamiento de usuarios en interiores y el control automático de asistencia como un ejemplo de aplicación de Smart Education. Por último, se busca enmarcar las pruebas realizadas dentro de un marco global predefinido (Des. 5). A continuación, se recogen los desafíos que se pretenden cubrir con esta tesis:

Des. 1. **Mejorar la localización de usuarios utilizando diversas tecnologías**: Este desafío se centra en encontrar formas de mejorar la precisión de la localización de los usuarios al combinar diferentes tecnologías radio en un instante específico. En lugar de depender únicamente de una tecnología, se busca aprovechar múltiples tecnologías simultáneamente para obtener una ubicación más precisa.

Des. 2. **Desarrollar un sistema de obtención de medidas de diferentes tecnologías**: Para lograr la localización precisa utilizando múltiples tecnologías, es necesario desarrollar un sistema que permita capturar las mediciones de estas tecnologías simultáneamente para su posterior procesamiento.

Des. 3. **Caracterizar diversas tecnologías precisas y comprobar sus ventajas y desventajas**: Una vez recopiladas las mediciones de las diferentes tecnologías, es importante analizar y caracterizar cada una de ellas. Esto implica estudiar sus capacidades, limitaciones, ventajas y desventajas para comprender mejor su funcionamiento y determinar qué nos ofrece cada tecnología en cada uno de los escenarios propuestos.

Des. 4. **Desarrollar aplicaciones reales basadas en localización**: Se pretende crear servicios y aplicaciones basados en localización precisa en tiempo real que puedan aprovechar los beneficios de la multitecnología. Estas aplicaciones tienen un amplio alcance y pueden estar dirigidas a diversos sectores, incluyendo servicios para el público en general, educación, construcción o situaciones de emergencia, entre otros.

Des. 5. **Conseguir un marco predefinido para realizar pruebas de localización**: Se pretende establecer un marco global predefinido para llevar a cabo pruebas de localización. Esto implica definir un conjunto de criterios, protocolos y metodologías que permitan realizar pruebas comparativas de las tecnologías de localización en diferentes escenarios y condiciones, para evaluar su desempeño de manera justa y precisa.

Los servicios basados en la localización requieren una información de posicionamiento fiable, continua y precisa [18]. Para este fin, se han desarrollado varias tecnologías, como GNSS o UWB, y técnicas como RTK, reconocimiento de imágenes o trilateración, que tratan de proporcionar información precisa de localización [19, 20]. Sin embargo, los escenarios de interior presentan grandes desafíos debido a las dificultades en la propagación de ondas de radio, lo que resulta en que GNSS no pueda ofrecer una precisión adecuada y los errores pueden llegar a ser significativos, incluso de varias decenas de metros. Los escenarios de interior suelen contener objetos metálicos que reflejan y bloquean las señales, lo que produce efectos de multitrayectoria que pueden afectar negativamente a la estimación de la localización e incluso generar zonas sin información de localización disponible. Además, algunos escenarios interiores suelen ser dinámicos, con cambios constantes debido a la movilidad de las personas dentro del escenario, como en un centro comercial o en un campus universitario. En consecuencia, se han desarrollado varias tecnologías para abordar estas limitaciones y proporcionar servicios de localización precisos en entornos interiores donde GNSS no puede llegar. El cálculo de la posición de un usuario es directamente proporcional a la precisión de las medidas recogidas. En este trabajo, se han llevado a cabo siete objetivos que abordan los desafíos propuestos anteriormente. Para ello, se hace un estudio en profundidad sobre la viabilidad de combinar diferentes tecnologías que aportan diferentes rangos de precisión (Obj. 1) para mejorar la estimación final de la localización obtenida mediante trilateración así como la cobertura y la disponibilidad de los sistemas de localización en entornos interiores. Para ello, es necesario comprobar mediante simulaciones si se cumplen las principales premisas de mejora.

Dado que GNSS tiene limitaciones en cuanto a su capacidad para proporcionar posicionamiento en interiores, diversas tecnologías están compitiendo para convertirse en la tecnología predominante en este campo en los próximos años. Entre ellas se destacan dos tecnologías que actualmente presentan grandes prestaciones que son UWB y WiFi. Ambas tecnologías ofrecen un alto rendimiento, logrando precisiones de centímetros en este tipo de entornos, aunque presentan ciertos inconvenientes como el alcance, el consumo de energía o la implantación en el mercado. Mientras tanto, las redes 5G, aunque todavía están en una fase inmadura de despliegue, prometen ofrecer una precisión de pocos metros de error. En términos generales, la fusión de estas tres tecnologías debería mejorar los resultados obtenidos tal y como se busca comprobar en el Objetivo 1. Para ello, se deberá desarrollar un marco de trabajo o una aplicación (framework) que permita recopilar los datos de forma individual (Obj.2) de las diferentes tecnologías en escenarios reales.

A pesar de las buenas prestaciones que ofrecen UWB y WiFi, un objetivo de este trabajo es profundizar en el estudio y la caracterización de ambas tecnologías en diferentes escenarios para evaluar sus diferentes cualidades (Obj.3). Es por ello que se plantea estudiar ambas tecnologías en escenarios que son cambiantes por su propia naturaleza tales como escenarios de construcción y de emergencias, en los que no se puede realizar un modelo genérico. Para ello, se evaluará la precisión, el alcance y la capacidad de penetración a través de diferentes plantas de un edificio y escombros, utilizando el framework previamente diseñado para el objetivo anterior.

El propósito del estudio teórico y la caracterización de diversas tecnologías es su implementación en el mundo real. Es por ello que se propondrán sistemas para la detección y localización de víctimas en escenarios de emergencias (Obj. 4) y para mejorar el rendimiento de los estudiantes en un marco de una educación inteligente (Obj. 5). Para lograr este cuarto objetivo, se buscará reducir los tiempos de búsqueda al mínimo ya que en un escenario catastrófico, una de las tareas más complejas es detectar, identificar y localizar a las víctimas, especialmente en situaciones donde están atrapadas bajo los escombros. Este proceso es el primer paso en una serie de medidas, que incluyen evaluar el estado de la víctima, establecer comunicación, liberarla y trasladarla a un lugar seguro [21]. Por lo general, este primer paso se realiza mediante observación directa, y no existe ningún diseño para informar al equipo de rescate sobre posibles áreas en las que podrían encontrarse las víctimas. En cuanto al quinto objetivo, se realizará un estudio sobre cómo utilizar la localización en una educación inteligente en los próximos años. Una vez que se comprueben los avances y aplicaciones ya existentes para una educación inteligente, se propondrá algún servicio basado en la localización con el fin de mejorar la educación de los estudiantes.

Sin embargo, existirán muchas circunstancias en las que los usuarios no podrán localizarse de forma precisa debido a una falta de un equipamiento más avanzado. Por tanto, el posicionamiento que se puede obtener en estos escenarios se realizará con la información de la potencia de la señal recibida. Debido a que la potencia recibida puede no seguir un modelo de propagación determinista, en los casos en que las condiciones ambientales permanecen relativamente estables, se observa que ésta permanece constante a lo largo del tiempo. Por ejemplo, si consideramos una ubicación muy próxima a un punto de acceso WiFi y la potencia medida disminuye inusualmente debido a un obstáculo como una pared, este nivel de potencia permanecerá inalterado a lo largo del tiempo mientras el obstáculo permanezca inmóvil. Como resultado, cada punto en el espacio se asocia con un conjunto de valores emparejados que comprenden identificadores de puntos de referencia y niveles de potencia recibida invariables. Este tipo de técnicas altamente dependientes de mapas radio son muy costosas debido a la fase inicial de recogida de medidas en el escenario. Por ello, se pretende estudiar el impacto de técnicas de localización basadas en modelos (Obj. 6) que abaratan en gran medida esta primera fase inicial ya que permite localizar a los usuarios con mapas inicialmente incompletos.

En esta tesis se realizarán diferentes pruebas de concepto y se mostrarán diversos servicios y despliegues basados en la localización en diferentes escenarios, como son de interior, construcción y emergencias, gracias al sistema desarrollado para recoger las medidas del mundo real definido en el (Obj. 2). Con el aprendizaje adquirido, se desarrollará un marco conceptual para definir una arquitectura con el propósito de crear nuevos servicios basados en la localización (Obj. 7). Para ello, se llevará a cabo un estudio en profundidad de los diferentes casos de uso en tecnologías que todavía no han salido al mercado (por ejemplo, la tecnología 6G) para definir un sistema de validación en una fase temprana de la tecnología. Estos sistemas de validación serán bancos de pruebas o *testbeds* que se utilizan para probar y validar nuevas tecnologías, productos o sistemas en un entorno controlado y seguro antes de su implementación en un entorno real. Primero se definirán los requisitos de los diferentes servicios que podemos encontrarnos en los próximos años. A continuación, se propondrá una arquitectura que permite a la tecnología emergente enfrentarse a los nuevos desafíos y desplegar una infraestructura para validar de manera temprana los objetivos que se pretenden alcanzar.

Obj. 1. **Estudiar la viabilidad de la fusión de tecnologías en un entorno simulado**. En dicha simulación se deberá crear un escenario con diferentes tecnologías y diferentes grados de precisión para ver cuáles son los posibles beneficios de dicha fusión. Este estudio consistirá en caracterizar los rangos de dos tecnologías de diferente precisión. En este objetivo se pretende comprobar si la fusión oportunista de una localización imprecisa con rangos precisos consigue mejorar la precisión de localización de los usuarios. Para ello, se deberá estudiar la precisión del sistema de localización en aquellas zonas en las que una localización precisa no es posible pero sí se observa información útil de rangos precisos.

Obj. 2. **Desarrollar un framework para obtener medidas reales y poder estudiarlas**. Para poder llevar a cabo experimentos reales, es necesario la creación de un framework que nos permita obtener las medidas necesarias para un escenario concreto. Para ello, se deberá capturar aquellas medidas que puedan aportar información de la distancia desde un punto de referencia a un objetivo. Con este framework, se podrán llevar a cabo campañas de medidas en diferentes situaciones en los que se encuentren objetos de diversa naturaleza que conlleva reflexiones y atenuaciones como, por ejemplo, un escenario de interior. De esta forma, se podrá evaluar el rendimiento de la fusión de información de diferentes tecnologías.

Obj. 3. **Caracterizar las tecnologías de localización de interiores más prometedoras en diferentes escenarios**. Para comprobar la precisión de las tecnologías más precisas en el mercado actual, se propone realizar un estudio de UWB, WiFi y, a ser posible, la red 5G en diferentes escenarios como son un escenario típico de interior, un escenario complejo como una obra o un escenario excepcional como es un escenario de emergencia. Esto nos permitirá definir y comprobar diferentes características de dichas tecnologías como son su precisión, alcance y capacidad de penetración.

Obj. 4. **Evaluar la localización en escenarios de interior con mapas incompletos**. Para ello, se desarrollarán técnicas basadas en mapas radio y se propondrán algoritmos de localización basados en *Machine Learning* (ML) para la generación de modelos que pretende minimizar los costes en la fase inicial de recogida de datos y permite localizar en zonas del escenario que no han sido medidas.

Obj. 5. **Proponer un sistema de detección y localización de usuarios en escenarios de emergencia**. Para ello, se llevará a cabo un estudio del estado del arte en el que se encuentran este tipo de sistemas y servicios. Además, se propondrá un sistema que se beneficie de algunas tecnologías comúnmente utilizadas para localización en escenarios de interior gracias a su robustez ante atenuaciones y reflexiones.

Obj. 6. **Estudiar y proponer una aplicación basada en la localización para una educación inteligente**. Gracias al intenso estudio que se realizará basado en la localización, se estudiará la aplicabilidad de nuevos servicios basados en localización para mejorar el sistema educativo con tecnologías para una Smart Education.

Obj. 7. **Proponer una arquitectura flexible de bancos de pruebas o *testbeds* para comprobar la viabilidad de algoritmos basados en localización para tecnologías emergentes**. En este sentido, se realizará un estudio sobre servicios que se ofrecerán en la próxima generación celular (6G) y se propondrá una arquitectura flexible para poder probar la viabilidad de algunos algoritmos y técnicas. Esta arquitectura englobará un sistema predefinido en el que se podrán realizar pruebas y poder validar la tecnología de forma temprana pudiendo así enfrentarse a requisitos que demande la sociedad del futuro.

1.4 Estructura de la Tesis

Este documento se ha estructurado en varios capítulos para mejorar su comprensión, como se muestra en la Figura 1.1. En este primer capítulo se realiza una introducción al tema junto con la motivación que nos ha llevado a realizar este trabajo y se definen los objetivos del trabajo. A continuación, se presentan los antecedentes y conocimientos necesarios para comprender el resto de la tesis. En el Capítulo 2 se presenta una revisión del estado del arte de las tecnologías utilizadas en este trabajo para mejorar el servicio de localización. Además, en el Capítulo 3, se exploran diferentes desafíos que presentan las diversas técnicas de localización que serán la base para realizar la fusión de las tecnologías aplicadas en esta tesis. Estas técnicas y tecnologías formarán la base para la realización de las pruebas concretas que se validarán con los resultados obtenidos y servirán para presentar su estudio en publicaciones de calidad.

El Capítulo 4 corresponde a las publicaciones que se han llevado a cabo en este trabajo para cubrir los objetivos y sustentar esta tesis. Estas publicaciones se agrupan en un bloque único debido a que abordan diversos aspectos relacionados con la localización, desde su estudio y aplicabilidad en entornos simulados hasta su implementación en servicios como escenarios de emergencia o educación inteligente, así como el análisis de las tecnologías en diferentes contextos. Por ello, se ofrece una guía detallada sobre la relación entre las publicaciones y los objetivos y desafíos planteados en la tesis, así como las herramientas y tecnologías utilizadas en cada caso. Cada una de las publicaciones incluidas en este capítulo examina un problema específico, realiza una revisión en profundidad y detallada del estado del arte, presenta una solución al desafío y evalúa los resultados obtenidos. En el Capítulo 5, se presentan las publicaciones en el orden establecido en el capítulo para la justificación de esta tesis realizada por compendio que cubre los objetivos propuestos.

Finalmente, el Capítulo 6 resume los resultados clave de la tesis y presenta las conclusiones derivadas del trabajo realizado. Además, también se proponen nuevas líneas de investigación que pueden ser abordadas en el futuro gracias a los hallazgos obtenidos en este estudio.

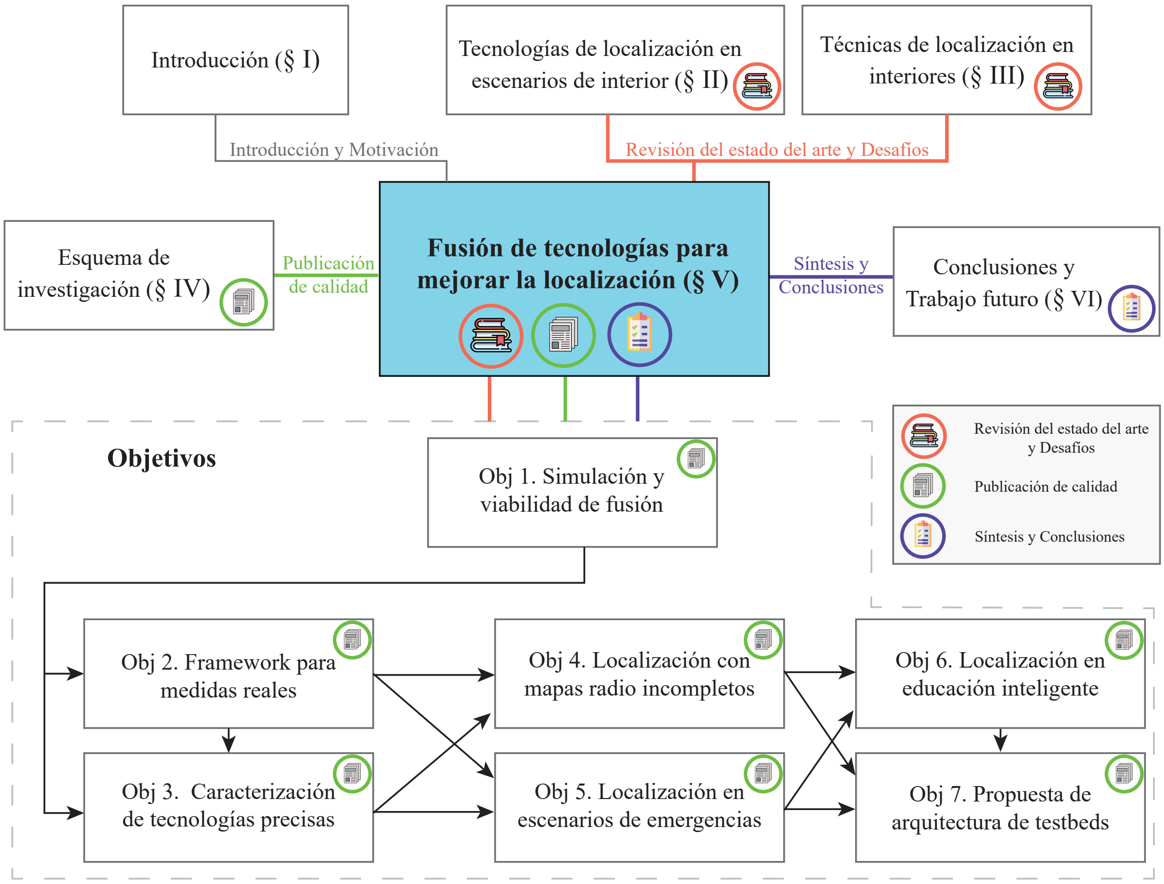


Figura 1.1: Estructura de la tesis

Capítulo 2

Tecnologías de localización en escenarios de interior

En los últimos años, a medida que los dispositivos móviles se han convertido en una extensión natural del ser humano, la localización de los usuarios se ha convertido en una dimensión clave en las comunicaciones. Con un crecimiento exponencial proyectado para el mercado de los servicios que se ofrecerán en el futuro gracias a una precisión submétrica, como la conducción autónoma [22] o la *eXtended Reality* (XR) [23], la localización precisa de usuarios se convierte en soporte clave para muchos de los servicios que consiguen trasladar al usuario y a su entorno al mundo digital. Esto abre una amplia gama de posibilidades para el desarrollo de aplicaciones cada vez más exigentes, que están destinadas a transformar nuestra vida cotidiana en el futuro.

En este capítulo se examinan diversas tecnologías empleadas para la localización de usuarios en escenarios de interior. Se comienza explicando por qué GNSS no es viable en espacios cerrados, seguido de un análisis detallado de varias tecnologías. Finalmente, se concluye con el impacto y la utilización previstas de estas tecnologías en el futuro.

2.1 Problemas de localización con GNSS

El posicionamiento ha constituido un reto para la humanidad desde el principio de los tiempos, resuelto en primera instancia utilizando diferentes cuerpos celestes como guía [24]. Sin embargo, con la introducción de la tecnología satelital GPS en los años 60, se estableció un sistema principal para la provisión de información de localización

[25]. En los últimos años, la tecnología GNSS ha experimentado un gran avance, gracias a la modernización de sistemas ya existentes como GPS o GLONASS [5] y a la implementación de nuevas constelaciones satelitales como Galileo [26] o Beidou [27].

GNSS es un sistema de satélites que orbitan alrededor de la Tierra y transmiten señales de radio para proporcionar información sobre su propia posición en el espacio. La localización por satélite básica implica resolver un problema geométrico basado en la distancia entre los satélites y un objetivo determinado como se muestra en la Figura 2.1 [28]. Para calcular esta distancia, se utiliza el tiempo que tarda la señal de radio en llegar al objetivo multiplicado por la velocidad de la luz (también conocido como tiempo de vuelo o *Time of Flight* (ToF)). El ToF se determina midiendo la diferencia de tiempo entre el envío del mensaje desde el satélite y su recepción en el receptor. Además, cada satélite utiliza un código identificador que permite a los receptores saber qué satélite está emitiendo la señal y proporcionar información sobre su órbita [29]. La posición de los satélites es fundamental para calcular la posición del objetivo mediante trilateración, un método que utiliza la posición conocida de los puntos de referencia (es decir, los satélites) y la distancia a ellos, que se explicará más adelante. Se requieren al menos cuatro satélites para determinar la posición del objetivo en tres dimensiones (3D) [30].

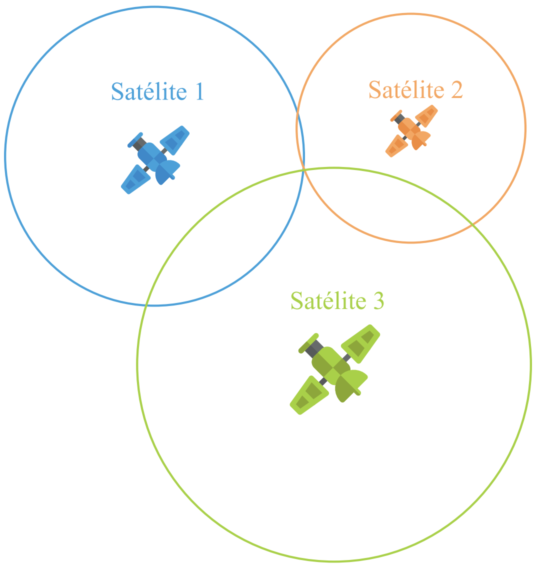


Figura 2.1: Posicionamiento básico con GNSS

A pesar de ofrecer un servicio global, el rendimiento de GNSS puede degradarse fácilmente debido a una gran variedad de factores. Así, los fenómenos naturales (por ejemplo, la influencia de las capas ionosférica y troposférica de la atmósfera [31]), la reflexión de la señal por multitrayectoria, el bloqueo de la señal con *Non Line* *of Sight* (NLoS) y las amenazas radioeléctricas (por ejemplo, las interferencias y la suplantación de identidad [32]) constituyen importantes retos para el GNSS. Dependiendo del tipo de observación por satélite que se utilice y del conjunto de datos de corrección que se aplique, se puede enumerar una amplia variedad de técnicas de navegación [5, 28]. Aunque técnicas como RTK pueden lograr una precisión de centímetros en espacios abiertos de manera casi instantánea, su viabilidad se limita a lugares donde hay visibilidad del cielo sin grandes bloqueos y requiere unos equipamientos altamente costosos [33]. En consecuencia, en zonas de interior, los obstáculos hacen que el margen de error en la localización de usuarios aumente significativamente, lo que limita la eficacia de técnicas precisas como RTK. A pesar de que GNSS se ha convertido en un estándar común para la localización en exteriores, el campo de la localización en interiores sigue siendo un área abierta a la investigación, con varias tecnologías compitiendo por su desarrollo.

2.2 Tecnologías para la localización de usuarios en interiores

Dado que la información satelital se ve muy condicionada debido a los bloqueos de los edificios, desde hace unos años existen varias tecnologías que buscan convertirse en el estándar de posicionamiento en interiores como sucede con GNSS en la navegación de exteriores. A continuación, se detallarán las características de estas tecnologías.

2.2.1 Red Celular

Una de las tecnologías más prometedoras para la localización en interiores son las redes móviles gracias a su ubicuidad. Las redes celulares 2G, 3G y 4G operan en un amplio espectro de frecuencias, que van desde los 800MHz hasta los 2600 MHz. Sin embargo, los esfuerzos de investigación y desarrollo de estas generaciones celulares se han enfocado en los servicios de voz y en el tráfico de datos para el consumo humano, lo que ha dejado en segundo plano el desarrollo de la localización precisa. Actualmente, la precisión de la localización con la red celular *LTE-Advanced* (LTE-A) de forma autónoma sin el apoyo de GNSS en escenarios de interior es inferior a 50 metros en al menos el 40% de los casos [18].

En la actualidad, el uso generalizado de la localización en muchos servicios ha generado una demanda de localización precisa para la nueva generación de redes móviles

5G [34]. Servicios como el beamforming [35] o control de flotas [36], necesitan la localización de los *User Equipment* (UE)s para poder gestionar la red de forma más eficiente.

Dado que la red celular no posee un sistema de localización preciso, en la última década, el 3GPP decidió incluir la información satelital como parte del protocolo para obtener la ubicación de los usuarios [37]. En la Release 15, la red celular utiliza la tecnología GNSS que se transmite a la red a través del protocolo de posicionamiento *LTE Positioning Protocol* (LPP) [38].

A pesar de que nos encontremos en una fase temprana de despliegue del 5G, el 3GPP ha anunciado que ofrecerá una precisión de menos de 3 metros en ambas dimensiones horizontales y verticales, y de hasta 10 metros en el plano vertical en espacios abiertos para el 80% de los casos [10]. Para ello, se implementarán distintos protocolos, como el multi-*Round Trip Time* (RTT) [39], que utiliza marcas temporales para medir la distancia entre la celda servidora y las celdas vecinas, y así mejorar la precisión del sistema. El 3GPP ha señalado en informes técnicos, como [10], que el uso de RTT puede emplearse en ambos espectros de frecuencia definidos en 5G, *Frequency Range* (FR)1 para frecuencias inferiores a 6GHz y FR2 para la banda milimétrica (mmWave). Este protocolo se utilizará en las señales de subida y bajada tanto de la celda servidora como de las celdas vecinas, con el objetivo de obtener una ubicación precisa de los usuarios sin que ello conlleve un mayor coste energético. Aunque se están preparando los fundamentos para el desarrollo de *Beyond 5G* (B5G) o 6G, los servicios basados en la localización en la red B5G/6G necesitarán información de posicionamiento fiable, continua y precisa para aprovechar todo su potencial [18].

Por otra parte, las redes móviles están evolucionando hacia celdas más pequeñas y, por tanto, estarán presentes en la mayoría de los entornos interiores. La implementación de frecuencias más altas como mmWave [40], junto con la capacidad de *beamforming* (gracias al *Multiple Input Multiple Output* (MIMO) [41]) y una alta densidad de celdas, permitirá una precisión muy alta en escenarios muy acotados. Esta implementación ayudará a reducir los errores de localización, incluso por debajo de un metro en la próxima generación de redes móviles (6G) [42]. Es por ello que se están llevando a cabo estudios y proyectos como Hexa-X [43] o Rise-6G [44] para prever cómo evolucionarán las redes celulares en los próximos diez años.

2.2.2 Bluetooth y BLE

Bluetooth es una especificación para las *Personal Area Network* (PAN), tal y como se estandarizó en la norma IEEE 802.15.1 [45]. Se trata de una tecnología de comunicaciones inalámbricas de corto alcance con un rango máximo aproximado de 100 metros para dispositivos de clase 1 [46]. Permite una comunicación de bajo coste y bajo ancho de banda para conectar dispositivos electrónicos como teléfonos móviles, auriculares, tabletas, ordenadores portátiles, impresoras, etc. Además, se pueden conectar varios dispositivos Bluetooth para formar redes malladas jerárquicas (Piconets) [47]. Desde su concepción inicial, Bluetooth ha experimentado diversas evoluciones en sus versiones con el objetivo de mejorar tanto su velocidad como sus características. La tecnología de posicionamiento Bluetooth localiza el objeto midiendo la intensidad de la señal [48]. En ambientes interiores complejos y cambiantes, los sistemas de posicionamiento Bluetooth se enfrentan a los desafíos de atenuaciones, reflexiones y bloqueos que hacen que tengan una baja precisión.

La versión más actual de la tecnología Bluetooth es conocida como Bluetooth de bajo consumo, o *Bluetooth Low Energy* (BLE). Esta versión tiene varias propiedades interesantes que han hecho que grandes empresas se centren en esta tecnología para mejorar la precisión de la localización de los dispositivos [49]. A diferencia de la tecnología Bluetooth ordinaria, en la que es necesario emparejar los dispositivos, en los dispositivos BLE pueden utilizarse en modo de difusión sin necesidad de emparejamiento. Además, BLE es una tecnología prometedora en las implementaciones del *Internet of Things* (IoT) [50, 51]. La localización mediante BLE se basa en mediciones de RSSI, que se pueden aplicar de diferentes formas en las distintas técnicas. Bajo condiciones específicas, se puede obtener una precisión de solo unos pocos metros de error, especialmente en *Line of Sight* (LoS) y con proximidad a balizas o puntos de referencia [52]. Esta tecnología es especialmente interesante en algunas aplicaciones ya que no requieren de un hardware costoso, además de que el número de dispositivos IoT está creciendo exponencialmente y muchos de ellos llevan integrado la tecnología BLE. Gracias a su amplio alcance, esto permite mejorar los sistemas de detección y aumentar la densidad de dispositivos que monitorean la ubicación de usuarios que no necesitan servicios de alta precisión, lo que resulta en una mayor cobertura y despliegue.

2.2.3 Banda Ultra Ancha (Ultra Wide Band, UWB)

La tecnología de banda ultraancha (UWB) es una tecnología radio de comunicación de corto alcance y gran ancho de banda que cuenta con pulsos extremadamente cortos (del orden de nanosegundos), lo que le otorga una fuerte resistencia a las condiciones de propagación con multicamino [53]. Esto puede ser beneficioso para calcular la distancia a un objetivo en entornos con características de propagación difíciles [54]. Para su funcionamiento, se utiliza un generador de ondas de alta frecuencia, que emite ondas UWB que ocupan un ancho de banda de frecuencias mayor a 500 MHz o al 20% de la frecuencia portadora.

Para evitar interferencias con otros servicios de radio, la Comisión Federal de Comunicaciones (*Federal Communications Commission* (FCC)) de EE. UU. ha restringido el uso sin licencia de la UWB a una densidad de potencia isotrópica equivalente de -41,3 dBm/MHz [55] y ha restringido la banda de frecuencias a 3,1 GHz - 10,6 GHz [56]. La Figura 2.2 muestra la coexistencia de la tecnología UWB con otros estándares de radiofrecuencia.

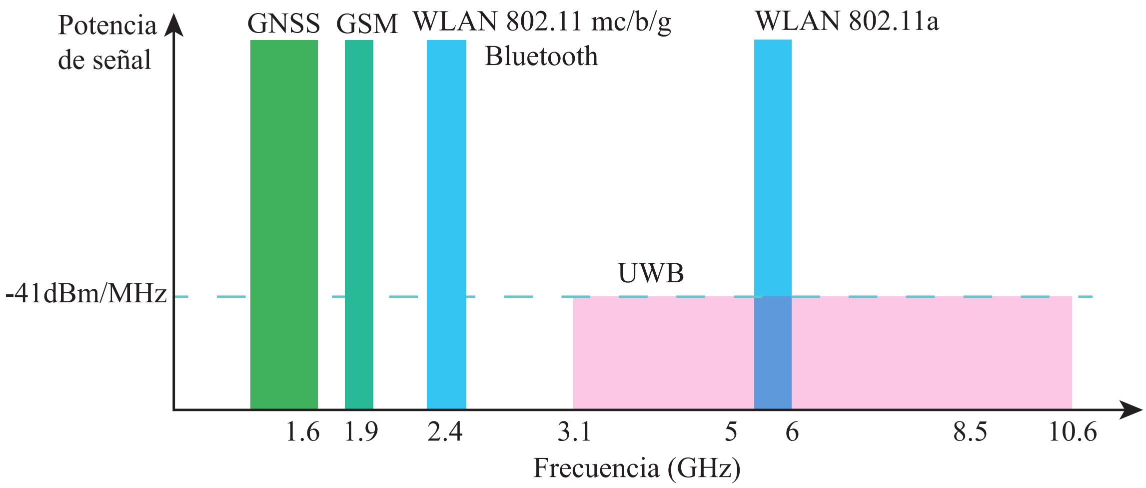


Figura 2.2: Espectro de frecuencias en los que operan varias tecnologías

Las restricciones legales en cuanto a la potencia de la señal limitan el alcance operativo a menos de 100 metros [56]. Por otro lado, la baja densidad espectral de potencia limita las interferencias de las señales UWB con otros receptores de banda estrecha [56]. Las señales UWB autorizadas operan en la longitud de onda de las microondas, lo que les permite penetrar materiales como el hormigón, el vidrio y la madera a través de los componentes de baja frecuencia en el espectro de la señal aunque a frecuencias más altas, esas capacidades desaparecen [57]. Uno de los motivos por los que UWB proporciona una precisión tan alta es debido a que utiliza el protocolo RTT en el que el paquete de datos se marca temporalmente en el momento de su envío a un receptor y este lo retransmite de vuelta pasado un tiempo concreto. De esta forma, se consiguen eliminar las derivas temporales entre los diferentes relojes ya que el único reloj que se utiliza para el cálculo de las distancias es el del transmisor. La tecnología UWB también es capaz de ofrecer un alto rendimiento para la transferencia de datos debido a su amplio espectro. El principal inconveniente es el elevado consumo energético que tiene asociado debido a la necesidad de un ancho de banda amplio para el intercambio de paquetes [58, 59]. El uso del protocolo RTT para localización incrementa aún más este consumo debido al intercambio de múltiples paquetes.

2.2.4 WiFi FTM

Debido a su rentabilidad, disponibilidad y actual despliegue mundial, la red WiFi ha sido sujeto de muchos estudios de investigación para mejorar el posicionamiento de interiores [60, 61]. Los sistemas de localización basados en WiFi pueden aprovechar la infraestructura ya existente en espacios interiores, lo que ofrece una cobertura global con costes muy reducidos para el operador. En las primeras versiones del protocolo WiFi (IEEE 802.11), la localización se estimaba mediante la potencia de la señal [60]. Los efectos de diversos elementos del entorno, como el cuerpo humano, los dispositivos electrónicos, puertas y materiales de construcción, han sido objeto de diversos estudios extensivos para mejorar la precisión de la localización [62, 63, 64]. Sin embargo, una localización basada en las mediciones de potencia, como se explica más adelante en los apartados 3.4 y 3.5, con constantes cambios en el entorno hace que sea inviable una precisión cercana al metro de error.

El estándar IEEE 802.11mc incluye la medición precisa del tiempo (*Fine Time Measurement* (FTM)) para la estimación de la distancia del UE al router mediante la inserción de marcas temporales y utilizando el protocolo RTT [65, 61] al igual que sucede en UWB. Esta versión pretende transformar el sector del posicionamiento en interiores en los próximos años, a medida que los nuevos equipos WiFi den soporte al protocolo IEEE 802.11mc de forma generalizada. El protocolo estima con una precisión en torno al metro [66] la distancia de cualquier usuario que soporte el protocolo WiFi FTM sin necesidad de estar conectado al router [67]. La información se calcula en la parte del UE para preservar la privacidad, ya que la información sensible sobre la ubicación no se comparte entre los nodos de la red. En [61, 68], se estima que la precisión para el posicionamiento WiFi FTM es de alrededor de un metro en escenarios del mundo real con despliegues densos de routers WiFi o *Access Point* (AP). Los dispositivos WiFi de Google lideran actualmente el desarrollo de esta tecnología, ya que fueron los precursores de dicho protocolo. No obstante, cada vez más routers están incluyendo este protocolo [69]. La tecnología WiFi FTM funciona sobre la banda de 5GHz y, en función del ancho de banda asignado, posee diferentes precisiones. Para las estimaciones de alcance con un 90% de error de *Cumulative Density Function* (CDF), se espera que tenga las siguientes tolerancias como se muestra en la siguiente Tabla 2.1.

Ancho de Banda [MHz]	Precisión del error [m] al 90%
80	2
40	4
20	8

Tabla 2.1: Comparación del nivel de precisión de WiFi FTM en función del ancho de banda [69, 66]

2.2.5 Conclusiones de las diferentes tecnologías

Las últimas tendencias del mercado muestran que la tecnología UWB puede convertirse pronto en un estándar de facto (aunque esta predicción está siendo desafiada recientemente por el IEEE 802.11 mc). Por eso, algunos smartphones ya han integrado chips UWB y WiFi FTM en sus móviles como Samsung o Xioami, en los últimos años. Las dos tecnologías UWB y WiFi FTM para la localización en interiores parecen ser también una rivalidad entre dos grandes empresas: Apple apuesta por UWB [70] frente a Google que lo hace por WiFi FTM [69]. Sin embargo, los últimos teléfonos de Google, los Google Pixel 6 y 7, ya constan de chips UWB integrados. WiFi FTM fue estandarizado por primera vez por la Wi-Fi Alliance en 2016 [66] y ha sido soportado en Android desde al menos 2018. Apple, con los AirTags y iPhones (a partir del iPhone 11 [71]) , comenzó a comercializar dispositivos que soportan UWB en el rango de 6-8,5 GHz a finales de 2019 [72, 73].

En los próximos años se espera que aparezcan nuevas aplicaciones basadas en *Localization-as-a-Service* (LaaS) en la futura red 6G. Se están proponiendo servicios como los vehículos autónomos [74], las redes sociales [75], servicios de salud *e-Health* [76, 77], la localización de víctimas en escenarios de emergencia (inundaciones, incendios, terremotos...) [78], realidad extendida en videojuegos [79], educación inteligente

[80] o la navegación de robots autónomos no tripulados [81]. Asimismo, la localización como una nueva dimensión también puede beneficiar a los procedimientos de gestión de redes, como la predicción del tráfico basada en la localización [82]. La Tabla 2.2 resume los requisitos de precisión y latencia, así como los desafíos que supone su implementación. Esto indica que en el futuro, diferentes tecnologías tendrán que coexistir para poder cumplir con los requisitos de los usuarios.

	Requisitos de ubicación (más restrictivos)		Desafíos de la investigación
Caso de uso	Precisión	Latencia	
Coches de conducción autónoma	< 1 m	< 100 ms	Coexistencia con conducción humana
Redes sociales	< 10 m	< 5 s	Detección de bots, privacidad del usuario.
e-Health	< 1 mm	< 50 ms	La cirugía a distancia tiene unos requisitos muy elevados
Escenarios de emergencia	< 5 m	Pocos segundos	Falta de infraestructuras, víctimas bajo los escombros
Sensores hápticos y juegos	< 10 cm	< 20 ms	Requisitos muy restrictivos en el interior
Educación inteligente	< 10 cm	< 20 ms	Requisitos muy restrictivos en interiores, alta densidad de usuarios
Robots autónomos	< 10 cm	< 50 ms	Escenarios interiores con mucho desorden

Tabla 2.2: Resumen de los requisitos y retos de los casos de uso de la localización 6G

Capítulo 3

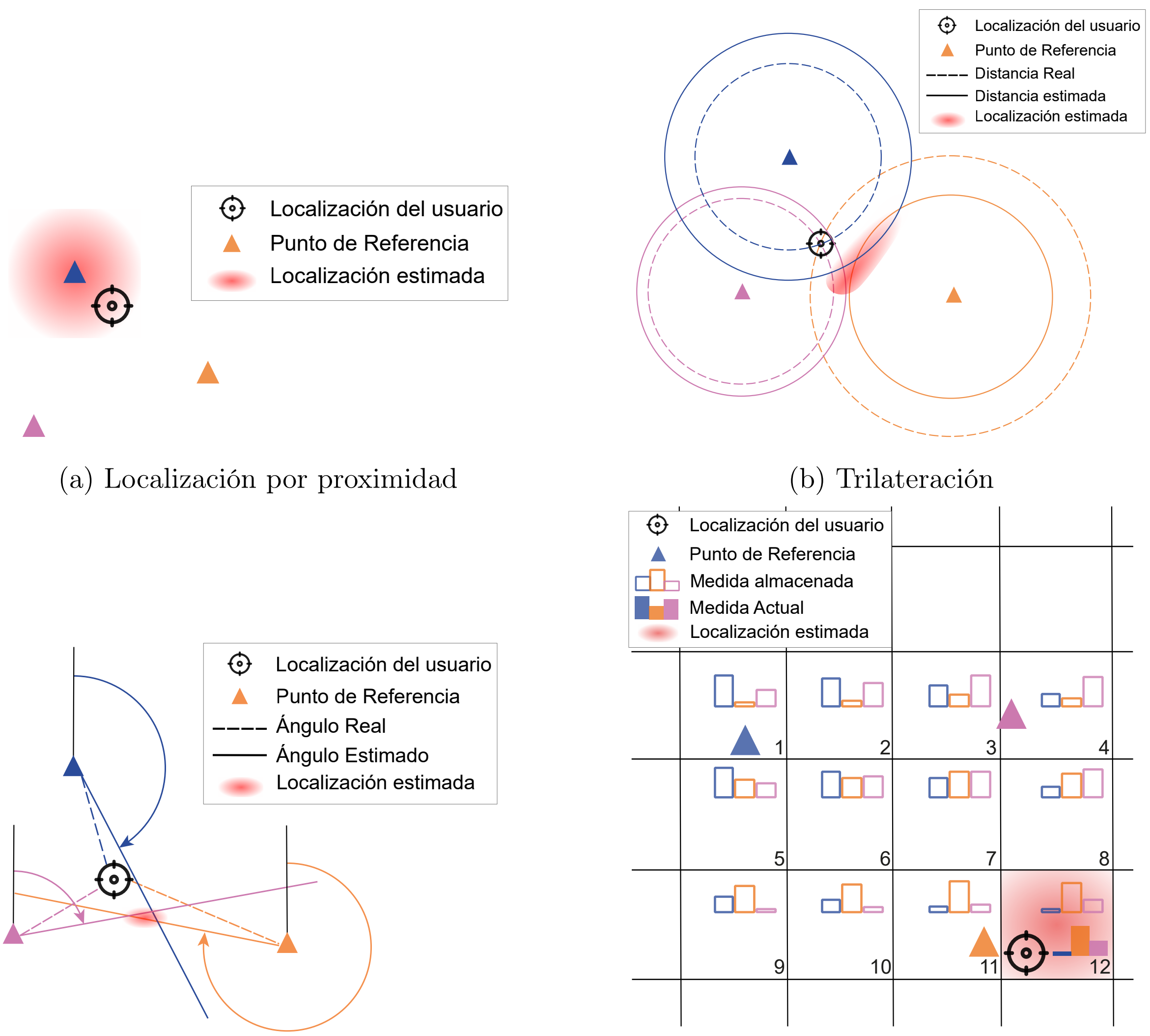
Técnicas de localización en interiores

En los últimos años, las necesidades del ser humano de posicionamiento han cambiado significativamente de exterior a interior. Tras conseguir un sistema robusto y fiable en exteriores como es GNSS, la tecnología se enfrenta ahora al reto de proporcionar una localización precisa en entornos interiores, donde no existe el apoyo de GNSS. Debido a esta necesidad de precisión en la localización de personas y objetos en espacios cerrados, se ha producido un gran avance en el desarrollo de diversas técnicas y tecnologías para lograr la localización efectiva en interiores.

Existen múltiples técnicas para localizar a los usuarios. En este capítulo se tratan las distintas técnicas de localización más utilizadas que consiguen una estimación de la localización del UE gracias a un conjunto de lecturas sobre los puntos de referencia. Hay varias técnicas que pueden utilizarse, en función del tipo de información y los recursos disponibles así como de los requisitos de rendimiento. La Figura 3.1 ilustra y resumen las principales técnicas de localización estudiadas en esta tesis.

3.1 Localización por proximidad

La forma más sencilla de localización es por proximidad a un punto de referencia (Figura 3.1a). La localización por proximidad obtenida en este caso es igual a la posición de dicho punto de referencia, ya que es el punto de menor distancia al resto de puntos del área. La estimación de la posición sucede en un área de cobertura del punto de referencia con diferentes grados de certeza. Los puntos más alejados del punto de referencia tendrán una certeza menor, porque la probabilidad de detección se reduce



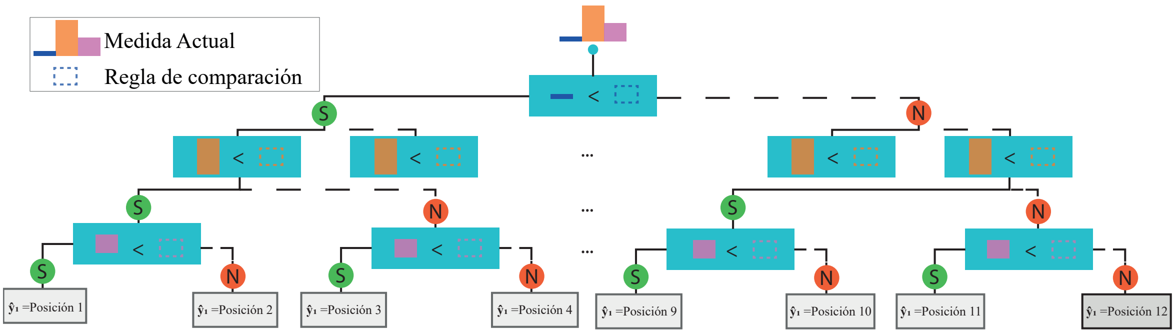
(a) Localización por proximidad

(b) Trilateración

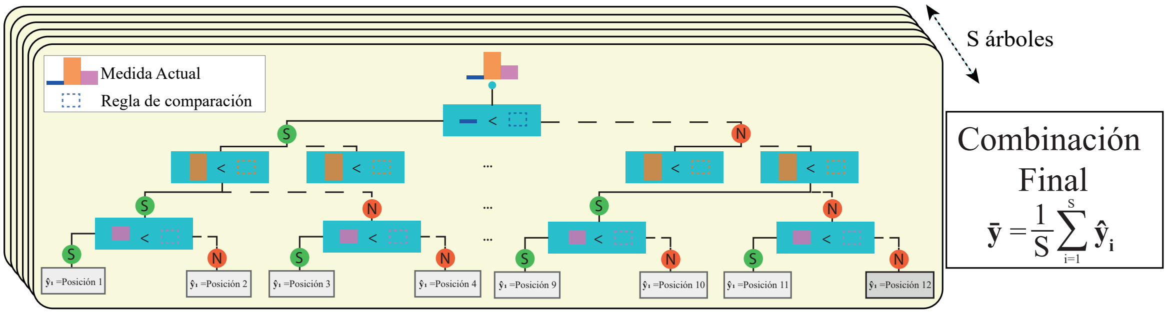
(c) Ángulo de llegada/salida

(d) Fingerprinting

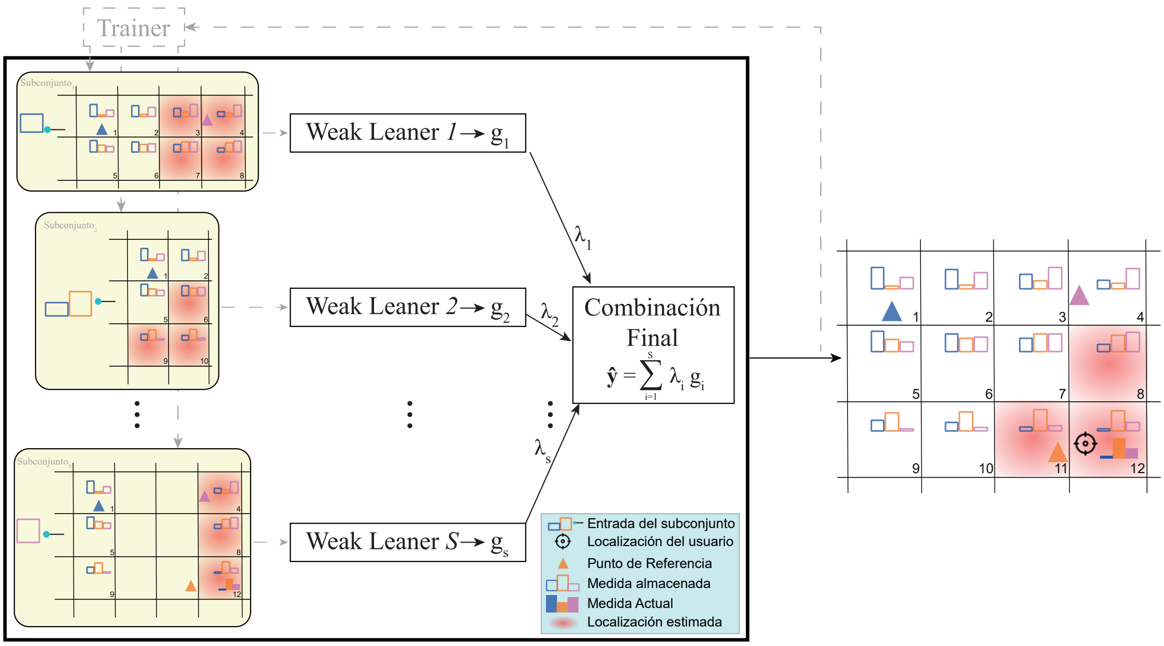
Figura 3.1: Principales técnicas de localización



(e) DTR



(f) Random Forest



(g) Adaboost

Figura 3.1: Principales técnicas de localización con la distancia. Esta técnica se utiliza, por ejemplo, en las redes móviles mediante técnicas como la obtención del identificador de celda o *Cell IDentification* (CID) para asumir la posición de un usuario dentro de un área de cobertura y ofrecerle una serie de recursos. Por ejemplo, en 2G cuándo un usuario llama al servicio de emergencias, se manda la localización obtenida con la red de forma que se tenga localizado al usuario en una región aproximada (<200 metros) [83]. Este tipo de técnicas también se pueden combinar con una base de datos de localizaciones conocidas, en Bluetooth Low Energy (BLE) [84, 85], para aplicaciones en las que la precisión no suele ser muy alta. Para este caso, un ejemplo claro son las audioguías los museos que basan la información que transmiten en función de la posición más cercana al punto de referencia o *beacon* [86].

3.2 Trilateración

Este método de localización se basa en el uso de distancias o rangos como se muestra en la Figura 3.1b. El rango a cada punto de referencia (de posición conocida) define una circunferencia sobre la que se puede localizar el objetivo. La intersección de cuatro esferas (o tres circunferencias en localización 2D) se utiliza para estimar la ubicación del objetivo. Para medir la distancia utilizando tecnologías inalámbricas, existen varios métodos disponibles:

- Estimación basada en la potencia (*Received Signal Strength Indicator* (RSSI)): este método estima la distancia a un punto de referencia basándose en la atenuación que sufre la señal hasta que llega al objetivo. Para ello, se parte de una potencia de transmisión conocida y se invierte un modelo de propagación adecuado al tipo de tecnología radio, la frecuencia y el entorno en el que se encuentra el dispositivo. El modelo de propagación debe seleccionarse teniendo en cuenta factores clave como la existencia de línea de visión directa así como el tipo de escenario en el que se encuentra el UE. A pesar de que este método se utiliza con frecuencia en redes móviles, Bluetooth o WiFi (excepto en WiFi FTM), su margen de error es elevado debido a la rápida atenuación de la señal y a la propagación multitrayecto. [87, 88, 89, 90].

- Mediciones de tiempo de vuelo (Time of Flight (ToF)): este método se basa en calcular el tiempo que tarda una señal en viajar desde un punto de referencia hasta el objetivo, y tiene la ventaja de ser más resistente a las interferencias, condiciones de multitrayecto y atenuaciones frente a otros métodos. Incluso con

NLoS, la precisión es mayor que con los métodos basados en la potencia [91]. Aunque la medición directa de ToF requiere una sincronización muy precisa entre el objetivo y los puntos de referencia, lo que puede resultar costoso, se puede utilizar el protocolo RTT para medir el tiempo de ida y vuelta de la señal y estimar el ToF en ambos sentidos utilizando solo el reloj del extremo transmisor. De esta forma también se cancelan las derivas que puedan sufrir los relojes frente a un reloj de referencia. Esta técnica se emplea en tecnologías como UWB [92] y WiFi-FTM [69], que pueden lograr una precisión de un metro aproximadamente. El ToF también se ha probado en 5G [93] para estimar la localización de los UE.

- Diferencia entre Tiempos de Llegada (*Time Difference of Arrival* (TDoA)): Una forma alternativa de calcular las distancias es estimar la diferencia de ToF de una señal entre diferentes puntos de referencia y el objetivo [94]. Esta diferencia se puede traducir en una diferencia de distancias, que se utiliza para definir una hipérbola en lugar de una circunferencia en el que se encuentra un usuario. La posición del usuario se puede estimar mediante la superposición de estas hipérbolas en lugar de circunferencias [95]. Aunque esta técnica es precisa, requiere que los puntos de referencia estén sincronizados con precisión para minimizar posibles errores.

No obstante, los rangos pueden contener errores por diversas razones, como la imprecisión y deriva de los relojes, bloqueos, desvanecimientos, reflexiones, etc. Estos errores pueden provocar que las circunferencias o hipérbolas utilizadas en la trilateración intersecten en múltiples puntos o en ninguno, como se ilustra en la Figura 3.1b para la localización en 2D, lo que genera áreas de incertidumbre representadas por el área roja. Los rangos reales se representan con líneas discontinuas, mientras que los rangos estimados con errores se muestran con líneas continuas. Los lugares más oscuros del área de incertidumbre indican una mayor confianza en la ubicación en función de la información disponible. Cabe destacar, que la posición real no se encuentra dentro del área de estimación, lo que refleja que habrá un error una vez resuelta la incertidumbre. Para resolver la incertidumbre, se pueden emplear técnicas como el método de mínimos cuadrados *Least Square* (LS) [96] o los mínimos cuadrados ponderados *Weighted Least Square* (WLS) [97], como se explica en el Capítulo 5.

Para realizar trilateración de forma efectiva, es necesario una cierta cantidad de puntos de referencia distribuidos en el área a cubrir, de forma que todos los puntos del área estén cubiertos al menos por cuatro de ellos (o tres en el caso de 2D). Esto puede suponer un desafío, especialmente en escenarios de interior, donde la presencia de obstáculos puede provocar bloqueos y desvanecimientos de la señal. Por ello, dependiendo del área que se quiera cubrir y de la capacidad de cobertura de las tecnologías disponibles, el costo de implementar dispositivos y la densidad requerida podrían ser elevados, o de lo contrario, podrían existir áreas sin cobertura.

3.3 Ángulo de llegada/salida

Es posible estimar el ángulo con el que la señal de los puntos de referencia llega al objetivo, conocido como ángulo de llegada (*Angle of Arrival* (AoA)), o el ángulo con el que el punto de referencia transmite una señal, conocido como ángulo de salida (*Angle of Departure* (AoD)). Los sistemas MIMO pueden estimar el AoA [98] o realizar beamforming [99], que consiste en seleccionar el haz o beam en el que se emitirá la señal, para obtener el AoD. A diferencia de la trilateración, para determinar la ubicación del UE se necesitan al menos tres mediciones en 3D, tal y como se muestra en la Figura 3.1c, o dos en 2D. Para esta técnica, al igual que en trilateración, el área de incertidumbre en las mediciones de ángulo puede resolverse mediante las técnicas de LS, WLS, etc. AoA se ha utilizado en simulaciones de 5G [100] logrando una precisión submétrica. Sin embargo, el AoA sufre en gran medida por las condiciones de multicamino y reflexiones [101].

3.4 Fingerprinting

En escenarios de interior, calcular distancias o ángulos se puede convertir en un reto especialmente difícil de superar que puede dar lugar a errores significativos. Aunque la medición de ToF reduce en gran medida estos errores, no siempre es viable, debido al elevado coste que supone el despliegue de dispositivos que soporten está técnica. Sin embargo, existen varias tecnologías que suelen estar disponibles en escenarios de interior, como oficinas y zonas residenciales, que ofrecen múltiples APs como son la red celular [102], WiFi [103] o Bluetooth [52]. Es por ello que un UE podrá ver un gran número de APs en este tipo de escenarios. Esto hace posible el aprovechamiento de estas señales para la localización del usuario.

Aunque la potencia recibida puede no seguir un modelo de propagación específico, si el entorno no cambia drásticamente, la potencia tiende a permanecer estática en el tiempo. Por ejemplo, si en un punto del escenario que está cerca de un AP de WiFi la potencia medida es anormalmente baja debido a un obstáculo como una pared, esta situación no cambiará con el tiempo si el obstáculo y el punto de acceso permanecen estáticos. Así, cada punto en el espacio $\boldsymbol{y}_i$ tendrá un vector asociado a las potencias recibidas $\boldsymbol{R} = (RSSI_1, RSSI_2, ..., RSSI_N)$ que indica la potencia recibida de la señal asociado a los diferentes N APs que no cambia con el tiempo. Este vector identifica a cada punto en el espacio con las medidas radio visibles en ese punto. Este mapa radio es la base del *fingerprinting* (Figura 3.1d).

La toma de medidas en *fingerprinting* tiene, por tanto, dos fases como se ilustra en la Figura 3.2. Una fase de entrenamiento, en el que se recoge un mapa con las medidas radio del entorno $\boldsymbol{R}$ (normalmente dividiendo el mapa en una cuadrícula de tamaño fijo), y una fase de explotación, en el que se comparan las potencias medidas $\boldsymbol{r} = (rssi_1, rssi_2, ..., rssi_N)$ en un momento determinado con cada uno de los puntos del mapa radio. Aquel punto que tenga mayor similitud con las medidas capturadas será la posición final del usuario. La precisión del sistema depende del tamaño de la cuadrícula y de sus divisiones definidas durante la fase de entrenamiento. Existe un compromiso entre la precisión y la complejidad, ya que una cuadrícula precisa también implica una fase de entrenamiento mucho más larga. Por tanto, *fingerprinting* puede alcanzar una gran precisión cuando la densidad de puntos de referencia es alta.

Aunque la técnica de *fingerprinting* puede lograr alta precisión con baja inversión en infraestructura, ésta presenta importantes limitaciones. El principal inconveniente es la compleja fase de entrenamiento, lo que restringe su aplicabilidad en ciertos escenarios, como en casos de desastres naturales donde la exploración previa es imposible, o en zonas rurales donde se debe cubrir una gran extensión. Otra desventaja relevante es que en escenarios cambiantes tanto de infraestructura, como en zonas de construcción, o de cantidad de usuarios, como centros comerciales, los valores de los mapas radio pueden variar drásticamente debido a los nuevos obstáculos en el escenario. Esto implica que la precisión no pueda mantenerse constante durante el tiempo o requiere de frecuentes reentrenamientos del mapa. Estos inconvenientes hacen que la técnica de *fingerprinting* no pueda ser escalable a nivel global como sucede con GNSS.

3.5 ML para la creación de modelos

La técnica de *fingerprinting* presenta una limitación significativa al requerir de un mapa radio completo sobre el entorno para su funcionamiento preciso. Incluso la omisión de un solo punto del mapa puede generar una cobertura incompleta e inducir a mayores

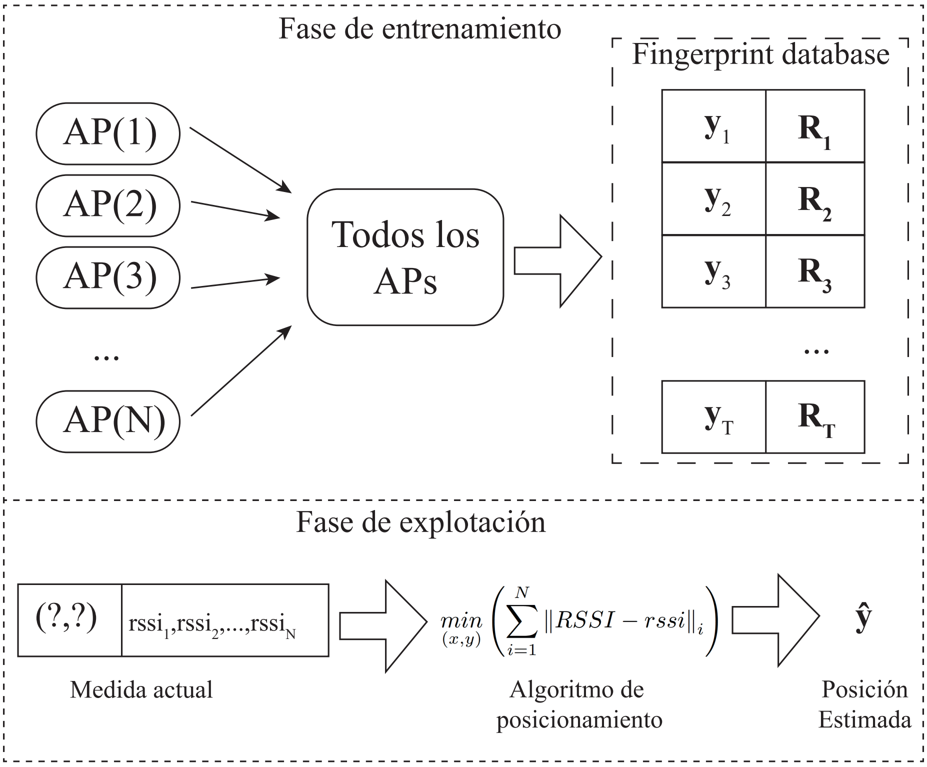


Figura 3.2: Fases de fingerprinting

errores, cuanto menos precisa sea la división del mapa. Para superar este problema, un enfoque comúnmente utilizado es emplear algoritmos de ML para crear un modelo del entorno, que luego puede ser utilizado para estimar la posición durante la fase de explotación. La creación de estos modelos reduce significativamente la necesidad de una campaña sistemática de medidas además de que pueden tenerse en cuenta otras variables para un mismo escenario como la hora del día u otras variables del entorno [104]. Este tipo de técnicas son reconocidas por su simplicidad y eficiencia computacional para estimar la posición [105].

Los *Decision Tree Regressor* (DTR)s utilizan una estructura de árbol para modelar el comportamiento del sistema dando como salida del sistema una posición ($\hat{\boldsymbol{y}}$) [106]. Esta estructura se genera a través de un conjunto de reglas de comparación jerárquicas que se aplican de manera secuencial. Cada regla, o rama del árbol, produce un resultado que conduce a un nodo final, u hoja, que determina la salida del regresor, como se ilustra en la Figura 3.1e. Al igual que en *fingerprinting*, el aprendizaje del DTR consta de tres fases: entrenamiento, validación y explotación. Durante la fase de entrenamiento, se utiliza un subconjunto de datos para crear un árbol tal que minimice el error de regresión. El subconjunto de datos de validación se utiliza para evaluar la eficacia del modelo. En este trabajo, se han estudiado diferentes algoritmos basados en DTR que fueron elegidos debido a su alta precisión y baja complejidad: *Random Forest* (RF) [107] y *Adapting Boosting* (Adaboost) [108].

3.5.1 Random Forests

RF es una técnica de ML que emplea una colección de modelos individuales (conocidos como *modelos base*) para generar una predicción final. Esta técnica de conjunto es especialmente útil para tareas de localización, ya que pueden combinar eficazmente las predicciones de múltiples árboles de decisión para determinar la ubicación de un dispositivo [109, 110].

La aplicación de RF es relativamente sencilla, ya que utilizan árboles de decisión, lo que las hace eficientes desde el punto de vista computacional. Además, RF es resistente al ruido de los datos, ya que emplea el método bootstrapping para generar árboles de decisión durante su fase de entrenamiento. Durante este proceso, se definen N características, que en el caso de la localización son los APs, que consisten en mediciones RSSI y la ubicación final del usuario. Para ello, se genera un número definido de árboles S entrenados en varios subconjuntos de los datos aleatorios con características y muestras diferentes. Para generar la predicción final ($\bar{\boldsymbol{y}}$) del proceso de localización, se promedian las predicciones de todos los árboles de decisión ($\hat{\boldsymbol{y}}_{\boldsymbol{i}}$), como se muestra en la Figura 3.1f. El promedio de todos los resultados de localización mitiga el impacto de cualquier árbol de decisión individual que pueda producir una estimación inexacta. Esta técnica es muy eficaz, lo que permite que pueda ser utilizada en aplicaciones en tiempo real.

A pesar de combinar múltiples modelos, RF puede ser eficiente computacionalmente dado que los árboles de decisión se entrenan en paralelo, por lo que el proceso de generación de modelos puede ser rápido [111]. Sin embargo, el modelo resultante puede causar problemas de memoria en caso de entrenar al modelo con una cantidad extremadamente grande de datos. Otro problema es justo el contrario. Con pocos datos de entrenamiento, los árboles de decisión suelen tender al overfitting más que otras técnicas.

3.5.2 Adapting Boosting (Adaboost)

Adaboost utiliza las predicciones de diferentes modelos individuales (g_i), conocidos como *Weak Learner* (WL)s, para llegar a una predicción final ($\hat{\boldsymbol{y}}$) [112]. Los WLs se generan mediante un proceso denominado *boosting*, que consiste en entrenar de forma iterativa el modelo con nuevos subconjuntos de datos, haciendo hincapié en cada ronda en los puntos de datos que se clasificaron incorrectamente en la iteración anterior. Gracias a esta iteración, se le asigna un peso asociado (λ_i) a cada WL que ajusta el regresor para minimizar el error. La Figura 3.1g ilustra el método de combinación de las predicciones de todos los WLs en el conjunto para hacer la predicción final. En esta tesis se estudian dos algoritmos de entrenamiento basados en Adaboost: *Decision Tree Adaboost* (DTA) y *Linear Tree Adaboost* (LTA). En el método DTA, las posiciones de varios WLs asociados a una regla de decisión se promedian en la predicción final [113]. DTA es útil cuando se trabaja con problemas de clasificación sobre posiciones utilizadas en la fase del entrenamiento como en *fingerprinting*. Por contra, el método LTA genera una función de interpolación entre las diferentes salidas dentro de un conjunto de reglas de decisión [114, 115] para obtener la posición final del usuario. LTA es más preciso que otros modelos en entornos parcialmente mapeados y cuándo la posición del usuario consiste en un problema de regresión, es decir, cuando no existe un número finito de soluciones finales. En este caso, el objetivo de LTA es predecir un valor numérico en lugar de una etiqueta de clasificación. Por tanto, DTA permite posicionar a los usuarios de forma precisa en posiciones previamente entrenadas frente a LTA, que predice la localización del usuario.

Adaboost posee la capacidad de adaptarse y aprender de los cambios en los datos a lo largo del tiempo [116], lo que lo hace crucial en entornos dinámicos donde las características inalámbricas son propensas a variar. Sin embargo, si no se controla adecuadamente, puede ser llegar al sobreajuste, reduciendo así la capacidad de generalización en nuevos datos y esto se verá reflejado en términos de precisión, a pesar de no ser algo típico de este modelo [117]. Además, es un modelo consistente frente al ruido o valores atípicos en los datos de entrenamiento de los modelos [112]. Aunque logra una gran precisión, especialmente en LTA, una desventaja significativa de Adaboost es sus altos requisitos computacionales [118] para la estimación final que lo deriva a un método inviable para aplicaciones en tiempo real.

3.6 Comparación de las diferentes técnicas

Las diferentes situaciones en las que se puede encontrar un usuario, los avances tecnológicos y la rigidez de los requisitos de los diferentes servicios hacen que no exista una única técnica óptima para localizar al usuario. La técnica de trilateración en los últimos años se ha convertido en una técnica muy utilizada por muchos ya que diferentes tecnologías como UWB o WiFi FTM permiten rangos de niveles submétricos. Por otro lado, con la llegada del 5G, las antenas pueden realizar *beamforming* lo que promoverá el uso de técnicas basadas en ángulos que hasta ahora no se habían explotado en gran medida. El gran auge de ML hace que técnicas como *fingerprinting*, que han sido de las más estudidas hasta la fecha, entren en desuso gracias a las técnicas basadas en modelos. La Tabla 3.1 muestra un resumen comparativo de las características de las técnicas de localización en interiores más utilizados.

Método	Medición	Precisión	Ventajas	Desventajas
Proximidad	Potencia de señal	Muy baja	- Simple y bajo coste - No es necesario una sincronización temporal	- Es un método muy dependiente al escenario ya que depende en gran medida de desvanecimientos y reflexiones
Trilateración	Distancia	Muy Alta	- El uso de marcas temporales hace que tenga una precisión alta.	- Necesidad de sistemas que soporten marcas temporales y protocolos para poder eliminar las desviaciones del reloj del sistema
Ángulo de llegada/salida	Ángulo	Alta	- Únicamente necesita de dos fuentes para una localización en 2D. - No es necesario una sincronización temporal	- Requiere condición de LoS - Las reflexiones anulan este método. - Necesidad de antenas con beamforming.
Fingerprinting	Potencia de señal	Media	- Sistema muy sencillo	- Necesidad de fase de entrenamiento extensa. - Cambios en el escenario requieren nuevos entrenamientos. - No escalable.
Random Forest	Potencia de señal	Media-Alta	- Sistema muy eficiente - Resistente a *overfitting* - Aplicabilidad en tiempo real	- Necesidad de muchos recursos para la fase de entrenamiento
Adaboost	Potencia de señal	Alta	- Se adapta a los cambios del entorno - Alta precisión - Menor frecuencia de reentrenamientos - Permite escenarios radioeléctricos grandes	- No apto para tiempo real. - Computacionalmente muy intenso.

Tabla 3.1: Resumen de las distintos métodos de localización

Capítulo 4

Esquema de la investigación

Este capítulo analiza detalladamente los trabajos desarrollados a lo largo de esta tesis así cómo las metodologías utilizadas y los desafíos que cubren cada uno de ellos. Este Capítulo está estructurado en dos partes. La primera, Sección 4.1, detalla los trabajos realizados en esta tesis y cómo se relacionan con sus objetivos. Cada artículo es descrito y se enfatizan sus contribuciones al campo de estudio. La segunda parte, Sección 4.2, presenta y explica la metodología de investigación utilizada, incluyendo las herramientas, técnicas y equipos utilizados para el desarrollo de esta tesis.

4.1 Descripción de las publicaciones

En esta sección se presentan los resultados obtenidos a partir de la investigación realizada en esta tesis convertidas en publicaciones de calidad en revistas. Para ello, se abordan los desafíos y objetivos previamente establecidos en la Sección 1. La Figura 4.1 muestra la relación entre los retos, objetivos y resultados alcanzados. El primer desafío con el que nos encontramos es con mejorar la localización de los usuarios mediante la utilización de diferentes fuentes de información, para ello, se ha realizado un estudio simulado para comprobar si conseguimos mejorar la localización de los usuarios fusionando la información de localización de diversas fuentes. Tras comprobar la viabilidad del sistema, se ha desarrollado un *framework* para obtener la información de localización de diferentes tecnologías para poder así caracterizarlas y desarrollar aplicaciones reales basadas en la localización. Por último, gracias a la experiencia adquirida durante todo el trabajo de esta tesis, se ha observado la falta de un marco común para realizar pruebas de validación de tecnologías de localización. Por ello, se ha propuesto una arquitectura flexible que permita verificar nuevas técnicas o tecnologías de localización en una fase temprana de desarrollo. Cada artículo de investigación se representa en la figura como un bloque individual dentro de una línea común que son los diferentes mecanismos y técnicas para una localización con multi-tecnología que cubren los desafíos y objetivos propuestos. En las subsecciones siguientes, se proporciona un resumen de cada una de las publicaciones que sustentan esta tesis. Los resultados obtenidos en **[I]**, **[II]**, **[III]**, **[IV]** y **[V]** son aquellos artículos ya publicados en revistas de alto impacto que sirven para avalar la tesis. Los otros dos artículos se encuentran en fase de revisión y cubren parte de los desafíos y objetivos propuestos.

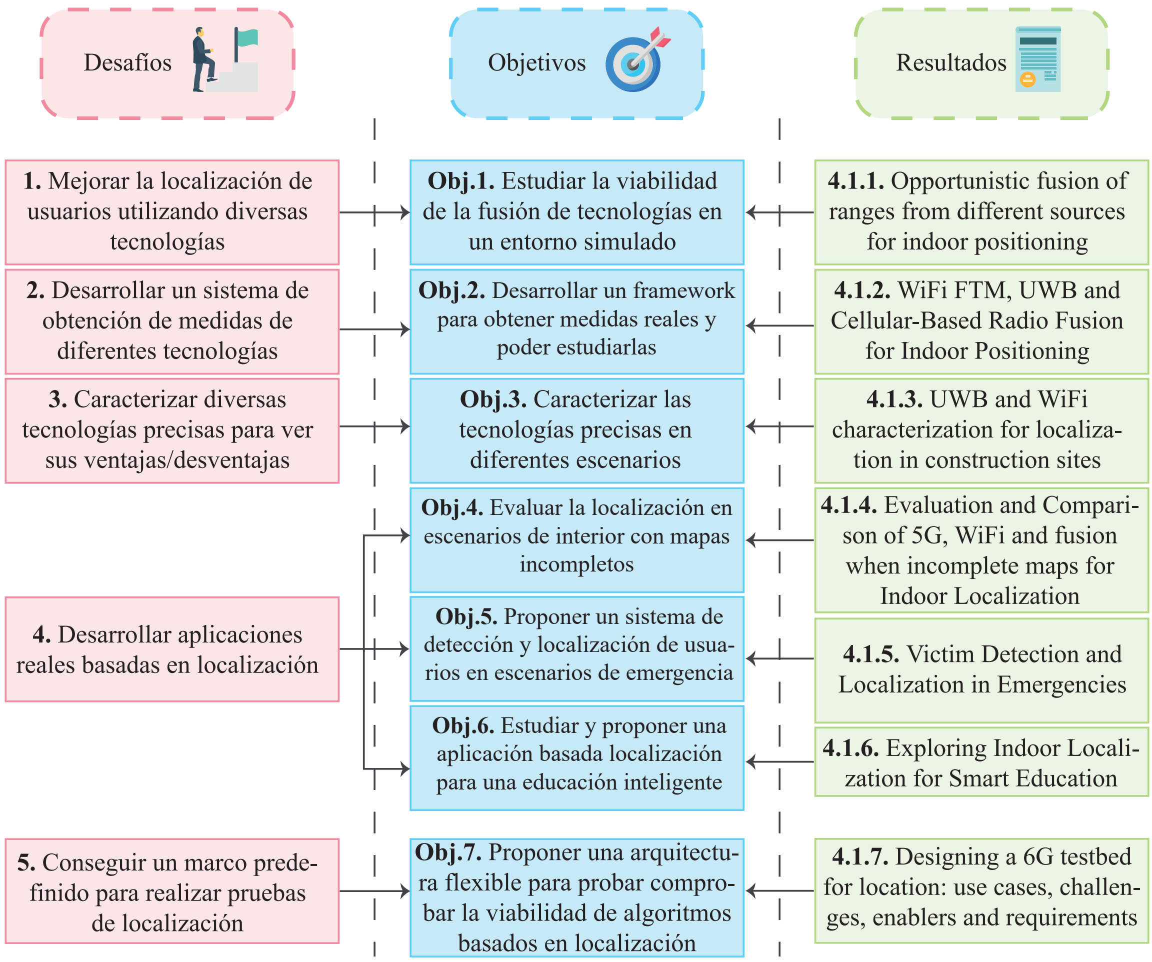


Figura 4.1: Objetivos, Desafíos y Publicaciones

4.1.1 Opportunistic fusion of ranges from different sources for indoor positioning [I]

Este primer trabajo cubre el primer estudio teórico para comprobar la viabilidad de realizar fusión de tecnologías en esta tesis. Este trabajo sirve como punto de partida para continuar con experimentos reales y desarrollar más en profundidad los futuros estudios relacionados. Para ello, primero se necesita conocer el contexto acerca de la localización mediante la fusión de tecnologías y, segundo, es necesario comprobar la mejora que se consigue mediante la fusión de rangos. Esta mejora no solamente se centra en términos de precisión, también se estudia la reducción de costes de despliegue, el aumento del área de cobertura y la disponibilidad del servicio de localización. Además, se abordan varias cuestiones como el aprovechamiento de los rangos precisos en zonas dónde la localización precisa no es posible (Obj. 1). En concreto, este artículo se centra en las tecnologías UWB y LTE como dos tecnologías contrapuestas. UWB posee una gran precisión pero las restricciones energéticas a las que puede transmitir impide que su alcance sea inferior a la centena de metros [119]. Por contra, LTE ofrece una mayor cobertura pero con unos rangos más imprecisos. Además, en este trabajo se propone un protocolo de comunicación dentro del *New Radio Positioning Protocol A* (NRPPa) para fusionar de forma directa la información de UWB en infraestructura de la red celular. Para realizar la fusión, tal y como se describe en el artículo, ésta debe realizarse en el mismo instante en el que se conocen las distancias a los puntos de referencia. De esta forma, cualquier dispositivo que ofrezca la distancia a un objetivo, independientemente de que sea UWB u otra tecnología, podrá utilizarse como fusión oportunista.

4.1.2 WiFi FTM, UWB and Cellular-Based Radio Fusion for Indoor Positioning [II]

En este segundo trabajo se lleva a cabo el diseño de un framework que recoge todas las medidas de LTE, UWB y WiFi para poder llevar a cabo un estudio con medidas reales (Obj. 2). Además, el desarrollo de este sistema de recogida de datos es crucial ya que nos permite caracterizar las diversas tecnologías fuera del entorno simulado. Este trabajo se puede considerar la evolución del trabajo anterior. Además, este sistema nos permite la creación de aplicaciones de localización de usuarios en tiempo real siendo la base para los trabajos futuros.

En primer lugar, se lleva a un escenario real el estudio de las distintas tecnologías.

En este caso, las distancias obtenidas mediante la red LTE se realizan mediante el estudio de la potencia disipada y modelos de propagación asociados a escenarios de interior. Por contra, UWB y WiFi utilizan medidas con marcas temporales para obtener la distancia hasta el UE. Estos rangos son precisos gracias a que se obtienen mediante marcas temporales y se basan en el protocolo RTT de forma que se consiguen eliminar las desviaciones y los offsets que puedan tener localmente algunos relojes. Este tipo de medidas, tal y como se muestra en el estudio, consigue alcanzar precisiones submétricas.

En segundo lugar, se realizó el estudio y análisis de diferentes técnicas de pesado basadas en la continuidad y la precisión que ofrecen las medidas a lo largo del tiempo. Esta información es muy útil para sistemas de navegación en escenarios estáticos ya que permite entrenar al sistema para reconocer si existen puntos de referencia que ofrecen malas medidas, ya sea por un fallo o una configuración errónea del dispositivo.

Por tanto, en este trabajo se demuestra que la fusión de tecnologías es muy útil para mejorar la localización en escenarios de interior y, por ende, la navegación de los usuarios a lo largo de este tipo de escenarios. Además, se demuestra como la localización final del UE mejora considerablemente añadiendo únicamente un elemento de alta precisión como un anchor de UWB o un router de WiFi en escenarios de baja precisión como es el caso de LTE.

4.1.3 UWB and WiFi characterization for localization in construction sites [III]

UWB y WiFi pueden considerarse tecnologías de localización según el criterio del 3GPP, que designa esta calificación a tecnologías de localización que alcancen un error inferior a 3 metros en el 80% de los casos tanto en el plano horizontal como vertical [120]. Sin embargo, en este tercer artículo se caracterizan ambas tecnologías para el posicionamiento en escenarios hostiles para la propagación de la señal como son los escenarios de obra (Obj. 3).

Gracias al framework desarrollado para cumplir el Obj. 2 en el anterior estudio, se permite realizar una investigación de UWB y WiFi tanto de su precisión, como de su alcance y capacidad de penetración en este tipo de escenarios. En términos de precisión, los resultados en este escenario se comparan con los obtenidos en el anterior trabajo debido a sus similitudes. En este escenario de obra, se muestra como los resultados obtenidos por UWB son sorprendentemente pobres en términos de alcance y capacidad de penetración. A pesar de que WiFi ofrece una estimación de la distancia al UE menos precisa que UWB, esta tecnología consigue cubrir en gran medida el escenario de construcción e incluso consigue llegar a distintas plantas para ofrecer el servicio de localización. La localización de los obreros en este tipo de escenarios es muy útil para poder advertirles de que se encuentran en zonas peligrosas por diversas causas como derrumbes o el paso de camiones o grúas [121]. Es por ello que una vez demostrado el comportamiento de UWB y WiFi para la localización de usuarios en escenarios complejos de construcción, se planteen estas mismas tecnologías en escenarios aún más complejos como son los escenarios de emergencia (Obj. 4). Para ello, ya se parte con un conocimiento previo sobre cómo funcionan ambas tecnologías en escenarios donde la señal sufre grandes variaciones debido a las condiciones de propagación.

4.1.4 Evaluation and Comparison of 5G, WiFi and fusion with incomplete maps for Indoor Localization [VI]

Existen casos en el que las medidas de distancias no están disponibles debido a la necesidad de un equipamiento más costoso. En estos casos, la localización basada en mapas radio toma mucho valor ya que permite localizar a los usuarios con medidas muy poco precisas como es el caso de la potencia de la señal recibida. Por ello, el enfoque de este artículo ha sido la dependencia con el mapa radio de técnicas como *fingerprinting*. Este tipo de técnicas son altamente dependientes de la granularidad del mapa radio. Una mayor división de cuadrículas se traduce en precisión de localización así como en un mayor coste asociado a esta primera fase de recogida de medidas. Por esta razón, se han estudiado diferente técnicas basadas en modelos de ML que permiten localizar a los usuarios en mapas radio con muy pocas muestras. Además, el uso de modelos para localización tiene otras ventajas como expandir el servicio de localización más allá del área medida, reducir los costes de reentrenamiento por cambios del entorno y reducir el número de puntos necesarios para modelar el mapa radio.

En este caso, el uso de fusión de tecnologías cobra mucho interés ya que, al igual que en los otros trabajos, la fusión de información en la entrada de los diferentes algoritmos demuestra que mejora la precisión de la localización de los usuarios, abarata costes de despliegue y aumenta la disponibilidad del tiempo de servicio.

4.1.5 Victim Detection and Localization in Emergencies [IV]

La gestión de catástrofes es un tema de la máxima importancia en la sociedad moderna. Naturalmente, a medida que avanza la tecnología, se encuentran nuevas aplicaciones para la gestión de catástrofes. Estas aplicaciones están sujetas a entornos muy difíciles en catástrofes, donde la infraestructura existente, como las estaciones base o los puntos de acceso, suele ser inaccesible. Además, el tiempo es un recurso limitado para las víctimas en todo momento. En este trabajo se hace un estudio de diferentes redes inalámbricas, en particular UWB, WiFi y LTE para poder llevar aplicaciones que sirvan de apoyo a los rescatadores en escenarios catastróficos. Gracias al estudio anterior, se conocían de antemano algunas características de las tecnologías UWB y WiFi. A pesar de todo, al ser mucho más complejo el escenario, se añadió la tecnología celular gracias a sus gran capacidad de cobertura y servicio. Sin embargo, en este caso concreto, LTE sufre tantas atenuaciones que no es posible llevar a cabo un estudio de sus características.

En este trabajo, se propone un sistema para detectar y localizar víctimas en escenarios catastróficos, más en concreto, en lugares sacudidos por un terremoto dónde las víctimas se encuentran bajo escombros (Obj. 4). Para ello, se realizó un estudio de las diferentes técnicas utilizadas, su grado de implementación y su precisión. Además, se propone un sistema que aprovecha las ventajas de diferentes tecnologías para un servicio de rescate rápido y preciso. Además, se hace un estudio de la tecnología BLE para su implementación para localización en la que queda descartada. Sin embargo, su uso para la detección de víctimas puede ser muy útil en este tipo de escenarios.

Para el estudio de este trabajo se ha replicado a un usuario atrapado entre escombros y se ha utilizado el framework para poder recoger medidas de las distintas tecnologías (para cumplir con el Obj. 2). En este escenario simulado, se enterró un teléfono móvil en una pila de escombros con elementos metálicos que dificultasen la propagación de las señales radio y degradasen las medidas. Como en el artículo anterior, la tecnología WiFi se postula como una tecnología muy poderosa en escenarios más complejos ya que posee una capacidad de penetración mayor y mantiene en buen medida los resultados a la hora de la localización de víctimas. Aún así, tal y como se indica en el artículo, utilizar diferentes tecnologías siempre es beneficioso ya que pueden complementarse para conseguir un sistema más preciso y eficaz, por lo que sigue demostrando la validez de nuestro primer estudio para cumplir con el Obj. 1.

4.1.6 Exploring Indoor Localization for Smart Education [VII]

La localización de los usuarios es crucial para el desarrollo de diversas aplicaciones e, incluso, de diferente naturaleza. Debido al carácter de esta tesis y en el marco universitario en el que se ha desarrollado, se ha investigado el uso de la localización para una educación inteligente. La amplia adopción de la tecnología WiFi y de la red celular, a la espera de ver cómo avanza la tecnología de UWB en los próximos años, hacen que ambas tecnologías sean cruciales en el posicionamiento de usuarios del futuro. En este trabajo se examina el potencial de la localización de interior en diferentes aplicaciones para llevar a cabo una educación inteligente (Obj. 5). Existen diversas aplicaciones como la navegación en espacios de interior (también abordada en el artículo **[II]**), la XR, los hologramas, el control de aforo o asistencia de forma automatizada. Por ello, se ha propuesto realizar una prueba de concepto basada en el control automático de asistencia para demostrar la utilidad del posicionamiento en este ámbito. También se ha investigado el impacto de la fusión de las tecnologías en diferentes algoritmos de ML para rastrear la presencia de los estudiantes en un aula y maximizar de esta forma los tiempos de aprendizaje, entre otros de sus posibles beneficios.

4.1.7 Designing a 6G testbed for location: use cases, challenges, enablers and requirements [V]

Tras la experiencia adquirida de los trabajos anteriores, una dificultad que nos encontramos ha sido la falta de entornos de experimentación y un framework de validación. Por ello, en este trabajo proponemos una arquitectura completa que sirva a lo largo de todo el ciclo de Investigación y Desarrollo (I+D) de tecnologías, técnicas y servicios de localización en redes móviles; más concretamente para la 6G que en la actualidad está en pleno desarrollo.

En este trabajo se hace un estudio sobre los requisitos y las necesidades de localización para los diferentes casos de uso que se pueden generar en la próxima generación de móviles 6G. Además, se tratan los principales aspectos que permitirán una localización que cumpla con las demandas del 6G como son el aumento de frecuencias y anchos de banda que mejoran la precisión de los rangos en técnicas como trilateración, la virtualización de diferentes elementos de red, el Open Radio Access Network (Open RAN) o el Edge Computing para mejorar el procesamiento de los datos para el servicio de localización y la coexistencia con otras tecnologías tal y como se trata en esta tesis para aumentar el número de dispositivos de referencia ofreciendo en el servicio de localización un aumento de precisión, cobertura y disminución de costes. Para ello, se propone una metodología que permita verificar en una fase temprana, si las técnicas y algoritmos propuestos para la localización de usuarios (Obj. 6) sirven para la tecnología propuesta. Esta metodología propone que las arquitecturas de los distintos *testbeds* pueden ser nómadas o cambiantes de manera que puedan ser exportadas a otras tecnologías que estén en desarrollo para verificar que se cumplen con los requisitos previamente definidos.

4.2 Metodología de investigación

La tesis ha seguido una metodología estructurada compuesta por varias etapas, como se puede observar en la Figura 4.2. A continuación, se detallan cada una de estas etapas:

- Revisión de antecedentes. En la primera etapa de la metodología, se llevó a cabo una revisión exhaustiva de los antecedentes sobre diferentes técnicas y tecnologías de localización así como la fusión de las tecnologías. Sin embargo, en la mayoría de trabajos disponibles en la amplia literatura se han centrado los esfuerzos en la fusión con los sensores inerciales como el acelerómetro y el giróscopo para el uso de la navegación como sistema de localización precisa.

- Formulación del problema. En esta segunda etapa, se descubrió la escasez de trabajos de investigación realizados acerca de fusionar diferentes tecnologías ya sea mediante rangos o, simplemente, información de potencia recibida. Por tanto, la falta de investigación en este campo permitió definir una serie de retos y objetivos para comprobar los beneficios que aporta la fusión de información con multi-tecnología para una localización precisa. Además, se propone verificar mediante simulaciones y experimentos reales la aplicabilidad de la fusión en diferentes escenarios. De esta forma, se definieron en detalle las cuestiones que debían investigarse y se planificaron los enfoques para resolverlas.

- Adquisición y preparación de los datos. La tercera fase de esta metodología consistió en recopilar y preprocesar los datos de las diferentes tecnologías para validar y evaluar los diferentes algoritmos propuestos.

Para el primer estudio inicial, se llevó a cabo una simulación que imitaba los datos de la red LTE y UWB en escenarios de interior. Para ello, se creó un entorno virtualizado en Python en el que se simulaba una red de LTE de exteriores y un sistema de localización de UWB tal y como se describe en **[I]**. Para la red LTE se simuló la atenuación de una señal en el espacio y para UWB se emuló la precisión de rangos obtenidos gracias a las marcas temporales de los paquetes de información con un modelo de propagación más preciso. Además, en este entorno se incluyó el filtro de Kalman, que es muy utilizado a nivel global por los expertos en localización por su sencillez y eficacia ya que permite predecir y corregir el posicionamiento de los usuarios en sistemas de navegación.

Por otro lado, para el desarrollo de esta tesis se han utilizado datos de diferentes redes reales obtenidos en distintos tipos de escenarios. Por una lado, se han realizado campañas de medidas de la red LTE y de la red 5G de la Universidad de Málaga en el marco del proyecto LOCUS [12] para escenarios de interior. Además, se han recogido datos de redes WiFi y UWB en el marco de diferentes proyectos. Además del LOCUS, se realizaron las medidas para los proyectos TEDES-5G [13], PENTA [14] y Maori [15], tal y como se puede observar en las diferentes publicaciones relacionadas con escenarios de construcción, emergencia y educación, respectivamente.

Es importante destacar que la recogida de datos es crucial para poder trabajar con datos reales. Es por ello que se desarrolló una aplicación móvil en Android Studio para recoger la información de las diferentes tecnologías presentadas en esta tesis como las redes móviles, UWB o WiFi FTM, entre otros. Nuestro principal interés ha sido la información de ToF o RSSI en los conjuntos de datos para localizar a los usuarios en los diferentes algoritmos propuestos. Las bibliotecas de Python y herramientas como scikit-learn [109, 122, 123] o pandas [124, 125] han sido muy útiles para el preprocesamiento de datos.

Otro requisito muy importante en los proyectos que han financiado esta tesis era la importancia de un posicionamiento en tiempo real por lo que, además de recoger los datos, se ha desarrollado un servidor capaz de recibir en tiempo real la información asociada a diferentes usuarios y localizarlos en los escenarios propuestos.

- Diseño del sistema. En esta etapa, se desarrollaron y emplearon sistemas y enfoques para abordar los desafíos previamente identificados. En este proceso se evaluaron diferentes técnicas de localización basadas en distancias, ángulos o potencias y diversos algoritmos como LS, WLS o el uso de ML para una ponderación más eficiente de los puntos de referencia para seleccionar la solución más adecuada en cada situación debido a los diferentes requisitos que nos podemos encontrar como precisión, disponibilidad o coste computacional.

- Evaluación. Durante esta etapa, se han sometido a validación y evaluación los sistemas propuestos, empleando diversos tipos de pruebas para tal fin.
  - Simulaciones. En el primer estudio, se realizó una simulación para dar validez a la técnica de fusión en primera instancia.
  - Pruebas de concepto. Estas pruebas implican evaluar el rendimiento de los algoritmos propuestos tras la recogida y post-procesado de los datos.
  - Revisión y mejora del estado del arte. Los sistemas propuestos durante este trabajo han sido el resultado de avanzar en la literatura con sistemas novedosos que fusionasen diferentes tecnologías a la hora de estimar la posición del usuario de forma instantánea e independiente, es decir, en el paso previo al uso de los filtros de navegación. De esta forma, se han mostrado así sus ventajas de mejoras de precisión, disponibilidad y reducción de costes frente al estado del arte.
- Difusión del conocimiento. Finalmente, los resultados más significativos logrados en el marco de esta tesis se han difundido en revistas especializadas y se han expuesto en congresos a nivel nacional e internacional.

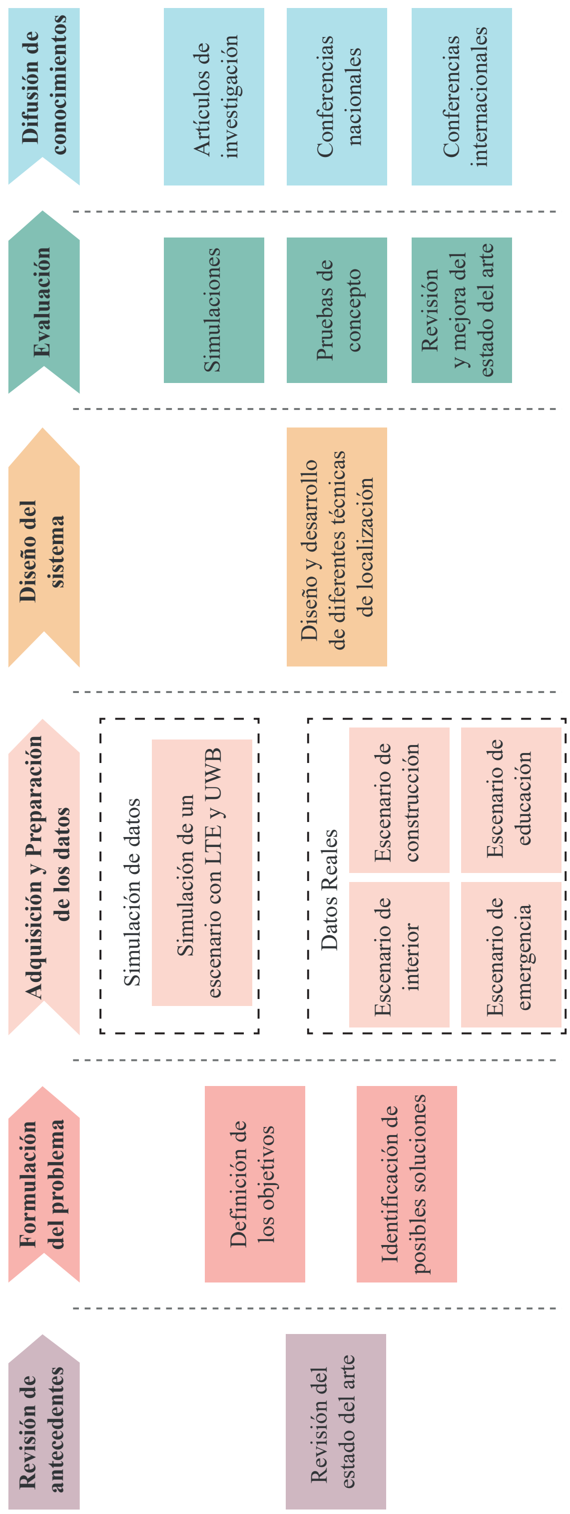


Figura 4.2: Objetivos, Desafíos y Publicaciones

Capítulo 5

Fusión de tecnologías para mejorar la localización

Opportunistic fusion of ranges from different sources for indoor positioning

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***Abstract*—Ultra-Wide Band (UWB) technology stands out as one of the most promising technologies for locating the user in indoor scenarios for the new 5G mobile generation. As a drawback, it requires a dense infrastructure. For this study, a simulation of a real environment with UWB and Long Term Evolution (LTE) base stations for positioning users is presented, tracked by an Extended Kalman Filter (EKF). The proposed method uses information that is unusable with UWB alone, and combines it with LTE location, improving the precision for the latter and enabling sparse infrastructure deployments.**

***Index Terms*—UWB, Position control, Location fusion, Indoor positioning, Mobile network.**

I. Introduction

The forthcoming 5G will require a precise indoor localisation method in order to enrich end-user services [1]. As Augmented Reality (AR) and Virtual Reality (VR) applications become popular, a need for cheap and precise network based localisation emerges. Global Navigation Satellite Systems (GNSS) have settled as the reference localisation system for outdoor environments providing an accuracy down to the metre. Nevertheless, the positioning error inside indoor areas increases in GNSS due to the harsh reception conditions [2]. In some mobile networks, such as Long Term Evolution (LTE), the network may locate users by estimating the distance to each base station (BS). Indoor positioning is characterised by high multipath, attenuation and shadowing originated by phenomena such as signal reflections on obstacles and walls, Non-Line-of-Sight (NLoS) conditions, sudden temporal changes in presence of people or changes in the environment [3]. In the near future, UWB technology may become the standard for indoor location as described by ETSI [4]. Nevertheless, UWB data has not been included yet in the New Radio Positioning Protocol A (NRPPa). NRPPa transmits positioning information from 3GPP and non-3GPP technologies available in the User Equipment (UE) such as GNSS to outperform the accuracy of mobile network location. In certain limited areas where a precise location technology (such as UWB) is deployed, GNSS or LTE positioning can be complemented or replaced by the local technology. In these cases, there are transition regions in the borders of the deployment where the information of a reduced number of reference points is available but the local technology cannot perform location. In this work, we propose a method that benefits from isolated UWB reference points (also known as *anchors*) in LTE scenarios for enhancing the precision of network-based positioning. Moreover, we also study the extension of the area in which the UWB anchors become useful.

Although there are many studies approaching location with radio-based technologies, there is no reference about fusing UWB and LTE for indoor positioning. In particular, both technologies have been studied separately, as seen in [5] and [6]. Indoor positioning is usually achieved with sources such as Wi-Fi, Bluetooth Low Energy (BLE) and pseudo-satellites, as described in [7]–[9]. In [8], different methodologies, such as fingerprinting or trilateration, which are the most commonly used location techniques, are applied. In some cases, location obtained with a single technology is combined with Inertial Measurement Units (IMU) in order to better track the movement of the user [10].

UWB systems give a centimetre-level accuracy over the area covered by the deployment [6]. The extremely wide bandwidth in UWB helps to deal with the multipath and fading effects on the signal, making it indispensable for indoor positioning. Therefore, some flagship smartphones are starting to integrate UWB chipsets, to provide an accurate positioning for the next generation of mobile applications. Nevertheless, deploying a mesh of UWB anchors has a very high cost, resulting in small, limited deployments. Conversely, LTE provides the user location with a large margin of error, but with a ubiquitous coverage [11]. A minimum of three ranging data items (reference coordinates and distances to the transmitters) are required at a single point in space to provide the location with trilateration. This limits the range of location below that of the simple addition of the coverage zones of the anchors, creating a zone in the border of the UWB network where energy is wasted. In this work, we fuse the ranging data of both LTE and UWB (low and high precise ranges, respectively) in zones where isolated UWB anchors do not provide location service but some ranging information is still available as shown in Figure 1.

The contributions of this paper are listed as follows:

- Optimisation and extension of the coverage area of high precision location by fusing data from isolated UWB anchors with ranges obtained from cellular networks.
- Improvement of the cellular-based positioning accuracy in the border of UWB deployments by leveraging the unused

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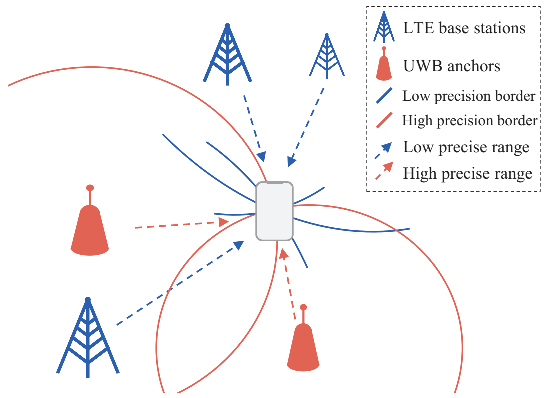

Fig. 1. Trilateration of a device fusing LTE (blue) + UWB (red).

data from edge anchors.

- A weighting scheme to prioritise ranging data depending on the technology and its precision.
- A modification of the NRRPa with the aim of including UWB into the standard to better benefit from the future availability of UWB chips in most smartphones.

Moreover, this method can be used to compensate missing LTE network elements that provide location with a sparse UWB deployment in some situations, such as in catastrophes.

The rest of this paper is organised as follows: Section II provides an explanation of the methodology. Section III shows the simulations that evaluate the proposed method. Finally, Section IV discusses the obtained results and the benefits of fusing the data in order to improve the indoor positioning areas.

II. Methodology

In this section, trilateration and EKF are described. Then, the fusion method for UWB and LTE is shown. Finally, a modification of the NRRPa to make use of the proposed method is introduced.

A. Trilateration and Iterative Weighted Least-Square

Trilateration is used for positioning a body with respect to a reference coordinate framework. To perform trilateration, the distance of the target to, at least, three reference points are required, as illustrated in Figure 1. Naïve trilateration in GNSS utilises the Time of Arrival (ToA) of the signal to estimate the distance to satellites whose positions are known beforehand; however, this method requires a very high precision in measuring time, forcing the need of atomic clocks. In [8] and [12], the range to the LTE BSs is estimated by means of the Received Signal Strength Indicator (RSSI) and propagation models that relate the RSSI with the distance. The main advantages of RSSI-based ranging are the simplicity and low cost for obtaining the received power from the BSs. As a drawback, LTE suffers from Inter-System Interference, fading and multipath, which modify the RSSI and add some ranging error. In contrast, UWB applies Two Way Ranging (TWR) protocol, which achieves centimetre-level precision in the range. Nevertheless, the lower coverage of a single UWB anchor implies that a much denser deployment is required in order to have all points in space covered with at least three signals. Each of the obtained ranges defines a circumference around its point of reference. In the ideal case where the distances are calculated without any error, the three circumferences will cut at the exact point where the target is located. In the more usual case where the ranges have some error and the circumferences do not cut at a single point, the system computes the Iterative Weighted Least-Square (IWLS) method in order to find the optimal solution as described in the next equations:

$$
\begin{aligned}
A &= \|\mathbf{p} - \mathbf{bs}_i\| \;;\; \forall i \\
\mathbf{y} &= \mathbf{p} - \hat{\mathbf{p}} \\
\delta\mathbf{p} &= (A^\top W A)^{-1} A^\top W \mathbf{y} \\
\mathbf{p}^+ &= \mathbf{p} + \delta\mathbf{p}
\end{aligned}
\tag{1}
$$

where A is the euclidean distance matrix from the computed position ($\mathbf{p}$) defined in 2D and the coordinates of the different BSs ($\mathbf{bs}_i$). The innovation vector $\mathbf{y}$ is the difference between the computed position and the estimated position ($\hat{\mathbf{p}}$) until the variation ($\delta\mathbf{p}$) does not exceed an arbitrary threshold. The weighting matrix (W) is $diag\left(\sigma^{-1}_{UWB_1}, \sigma^{-1}_{UWB_2}, \sigma^{-1}_{LTE_1}, \ldots,\ \sigma^{-1}_{LTE_n}\right)$. A reasonable choice for the weight matrix is $W = Q_{yy}$, the variance–covariance matrix of the measurements [13]. The goal is to give more confidence to the more precise measurements. Finally, $\mathbf{p}^+$ is the updated position for the next time interval.

B. Extended Kalman Filter

For tracking the location of a moving target, the noise (that is, the positioning error) of the sensors (which may be devices such as IMU, GNSS receivers or UWB tags), creates an uncertainty in position increasing over time. Bayesian Filters can cancel this cumulative error with a probabilistic estimation in dynamic scenarios with ambiguous measurements. Extended Kalman Filter (EKF) is the most used algorithm in navigation systems [13]. EKF is a recursive method which allows to estimate the new position of the user according to the new measurements and the previous state (position and velocity) of the user [14]. This algorithm follows a Markov chain pattern, in which the system has memory, but it only takes into account the previous state $\hat{\mathbf{x}}_{k-1}$. This filter works in two steps:

1) Prediction: Using the previous state $\hat{\mathbf{x}}_{k-1}$ which includes the position and the velocity of the user, the system computes the predicted state $\hat{\mathbf{x}}_k^-$ and updates the covariance matrix of the prediction P as follows:

$$
\hat{\mathbf{x}}_k^- = \begin{cases} \hat{\mathbf{x}}_k^- = F\hat{\mathbf{x}}_{k-1} \\ \hat{P} = FPF^\top + Q \end{cases}
\tag{2}
$$

where F is the state transition function and Q is the process covariance of the system.

2) Update: The update step consists in determining the position of the user with the compromise between the predicted state and the observation matrix $\mathbf{z}$. At this point, the Kalman Filter Gain (K) weights the measurements and the predicted state conforming to the quality of the observations. In case of inputs with poor quality, their weight will be low; otherwise, the input data will dominate over the prediction as shown in the next equation.

$$\begin{gathered} \mathbf{y} = \mathbf{z} - H\hat{\mathbf{x}} \\ K = \frac{\hat{P}H}{H\hat{P}H^{\top}+R} \\ \hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + K\mathbf{y} \\ P = (I - KH)\hat{P} \end{gathered} \tag{3}$$

where $\mathbf{y}$ is the residual vector between the prediction and the measurements, H is the measurement function, I is the identity matrix of $\mathbb{R}_{2x2}$ and R is the noise covariance matrix of the measurements.

C. Proposed fusion method

The proposed fusion method blends LTE and UWB ranges providing an over-determined system with more measurements than a technology in isolation. In this case, the trilateration algorithm uses ranges from different technologies as illustrated in Figure 1 in which LTE ranging data is complemented with data from UWB isolated anchors to improve the location accuracy. Figure 2 describes the algorithm divided in three steps. First, the ranging data is collected from the ranging devices (i.e. the LTE modem or the UWB tag). Second, trilateration is done using three UWB ranges if available. Otherwise, LTE ranges are used to complete the three required ranges. In this step, fusion is done between a precise technology with partial information (UWB) and an imprecise technology with ubiquitous coverage (LTE). Lastly, EKF updates the end-user position as described in the previous section.

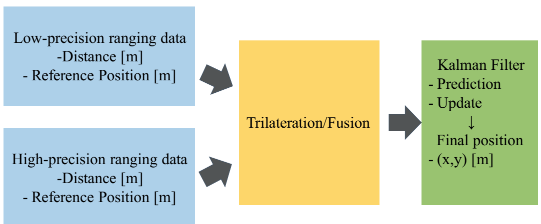

Fig. 2. Diagram of the fusion algorithm for positioning, step by step.

The proposed fusion achieves two things: in scenarios within an LTE network, a sparse UWB deployment can be used to improve location precision without reaching the density and cost required for a full UWB system; and a smooth transition with high precision is achieved between indoor and outdoor scenarios or between different location system areas as illustrated in Figure 3. The red zone is the area covered by UWB; throughout this area, all points have visibility of at least 3 UWB anchors. The yellow area is the zone where we apply the fusion algorithm. In this area, LTE location is complemented with the information from one or two anchors in the edge of the UWB deployment in order to improve the location accuracy. Finally, the rest of the scenario is covered only by LTE.

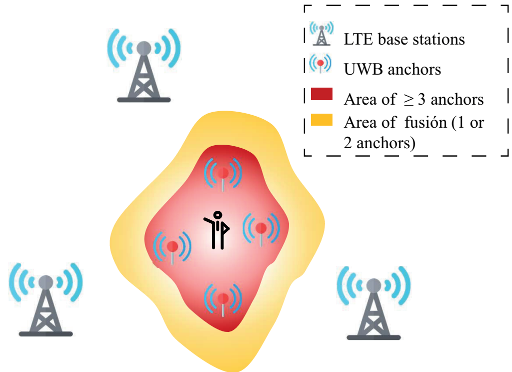

Fig. 3. Example of a LTE scenario with and UWB location area (red) and fusion location area (yellow)

D. NRPPa for UWB

Nowadays, 3GPP does not define any specification towards UWB. NRPPa establishes a mechanism by which the network may acquire a more precise location information from the UE. This precise location is obtained with GNSS receivers in the UEs. In this paper, we propose using procedures and messages similar to the existing NRPPa protocol for UWB such as those described in TR. 38.455 [15]. To allow fusing LTE ranges (that can be obtained by the mobile network) with UWB ranges (that can only be obtained in the UE), the following messages should be added as an extension to NRPPa:

- UE device unique identifier
- UWB anchor identifier
- UWB anchor location
- Timestamp
- Time of Flight (ToF)

Some optional fields could be used to transmit additional information that can be used to characterise the error of the UWB ranges, such as the frequency channel, LoS/NLoS conditions, etc.

III. Experimental Set-up

This section presents the evaluation of the proposed fusion of LTE and UWB location. Furthermore, the performance of EKF with respect to a memoryless system is analysed. Then, the performance of the proposed fusion method compared to LTE-only location method inside the area within the range of some UWB anchors.

A. Environment setup

According to the density of LTE stations described in [16], four BSs have been deployed approximately 100 m from each other. In addition, an UWB deployment within the LTE network is emulated, with four UWB anchors placed tens of meters from each other, as described in [17]. Figure 4 shows the map of the simulated environment. LTE BSs are represented by the pink triangles and UWB anchors by the green triangles. Table I lists the main parameters of the simulation in which P_{tx} is the transmitted power from the BS, f is the frequency of the technology, h_b is the height of the BS and $P_{rx_{min}}$ is the sensitivity of the system for each technology. LTE follows the Okumura-Hata propagation model [18]. For simulation simplicity, this model is used both outdoors and indoors, adjusting the error of location to the typical LTE indoors location error. UWB, on the other hand, follows the log-normal propagation model described in [3].

TABLE I
PARAMETER CONFIGURATION OF THE BASE STATIONS

Source	P_{tx} [dBm]	f [MHz]	h_b [m]	$P_{rx_{min}}$ [dBm]
LTE	47.4	1800	30	-84
UWB	-68.28	6000	5	-132.98

B. Simulation and results

In the scenario described above, a Monte Carlo method is used in order to set up a simulation that provides statistically relevant results, generating a thousand random trajectories with a hundred points for each trajectory. The simulated points follow a straight line between two random points inside the scenario. We also include an Additive White Gaussian Noise (AWGN) in the LTE and UWB received signals.

1) Use of Extended Kalman Filter: the gain of using an EKF is determined comparing it to a non-memory system, a system that does not use the information from a previous time interval. Table II displays the relevant statistical results of the experiment i.e. the mean and the standard deviation of the error, and the 2σ parameter that contains the 95% of the sorted error compared with the ground truth in both cases: in a non-memory system and an EKF system. In order to be efficient, the rest of the simulations employ EKF due to the better performance of the system.

TABLE II
COMPARISON OF THE HORIZONTAL ERROR BETWEEN NON-MEMORY SYSTEM AND EKF SYSTEM.

System	Mean	Std. Deviation(σ)	$2\ \sigma$
EKF	1.039	0.661	2.225
Non-Memory	1.489	1.036	3.529

2) Fusion location accuracy: Figure 4 shows the regions in which each technology acts. The scenario is composed of three different zones which follows the same distribution of Figure 3. The red dots are the points estimated only with UWB, while the blue dots are estimated by LTE. The yellow dots indicates the points where there are one or two UWB anchors visible and their ranges are fused with LTE ranges to provide location. In this area, the accuracy is expected to improve compared to LTE as long as we have more precise ranging information from UWB. Figure 5 shows the area where fusion (yellow) and UWB (red) are used independently. Figure 5 also shows the covariance error shapes (i.e. the confident contour). The error circumferences represent an outline of the Gaussian distribution

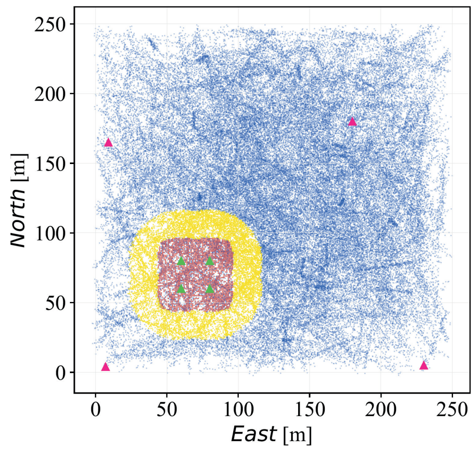

Fig. 4. Position tracked in LTE (blue), fusion (yellow) and UWB (red) over a Monte Carlo simulation.

and they contain the 99% of the points of each distribution. The shapes are typically ellipsoids, however, the square-shaped distribution of the UWB stations leads to this circular shape. This distribution was considered as the best option in order to better represent the improvement of the coverage area. The inner circle (green) separates the UWB coverage area (red). The outer circle (pink) wraps the points where LTE location has been improved with fusion with the available UWB information (yellow). The fusion radius is 50m compared with the UWB radius of 25m by using information that normally has been dropped, therefore, a noticeable increase in the area with high accuracy is observed.

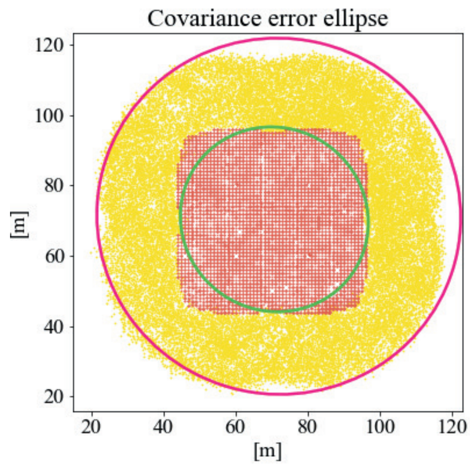

Fig. 5. Confidence circumferences of the position points in fusion (outer circle) and UWB (inner circle)

Figure 6 represents the cumulative distribution function (*cdf*) of the horizontal position error in LTE (blue), fusion (yellow) and weighted fusion (red) with respect to the ground truth in the yellow area or the transitional area between the only LTE to only

UWB. It can be observed that fusing incomplete information from UWB anchors with LTE ranges reduces the error with respect to using only LTE ranges. The green line represents 90% sample line, and the error for this point is reduced by 60cm and 90cm for fusion and weighted fusion, respectively.

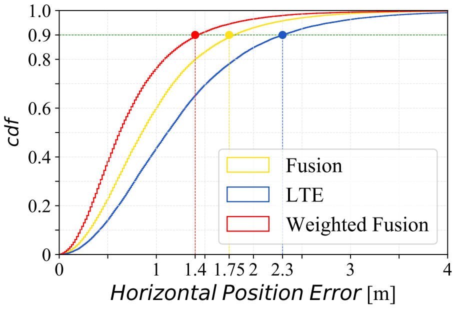

Fig. 6. Horizontal Position Error of LTE (blue), fusion (yellow) and weighted fusion (red).

The error distribution clearly follows a log-normal distribution. Table III shows the parameters to characterise the error of all the cases by their mean and standard deviation (σ) and the 2σ parameter which includes the 95% of the error. By using the remaining information of UWB anchors that were not used in the single-technology scenario, an overall enhancement of the system is achieved. In addition, giving more confidence to the UWB ranges by using a higher weight also improves the performance.

TABLE III
COMPARISON OF BETWEEN LTE, FUSION AND WEIGHTED FUSION HORIZONTAL ERROR.

Source	Mean	Std. Deviation(σ)	2 σ
LTE	1.015	0.637	2.196
Fusion	0.908	0.586	1.997
Weighted Fusion	0.763	0.553	1.997

IV. CONCLUSIONS

In this paper, the fusion of LTE and UWB data is proposed for enhancing cellular-based location. A modification of NRPPa is also proposed due to the role that UWB will take in the upcoming future thanks to its inclusion in the latest flagship smartphones. The use of this novel fusion in the trilateration algorithm noticeably extends the precise coverage area beyond what an UWB deployment can offer on its own. Furthermore, this technique does not require any additional hardware apart from UWB and LTE receivers. This allows a reduction of costs in network deployments oriented at providing location. Firstly, with this setup, a smaller number of UWB anchors is required to provide an accurate and precise location in a planned area. Secondly, in cases where an LTE network already provides location information, but an increase in precision is required, a sparse UWB network can be deployed such that at each point, one or two anchors are visible to use fusion.

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Article

WiFi FTM, UWB and Cellular-Based Radio Fusion for Indoor Positioning

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Abstract: High-precision indoor localisation is becoming a necessity with novel location-based services that are emerging around 5G. The deployment of high-precision indoor location technologies is usually costly due to the high density of reference points. In this work, we propose the opportunistic fusion of several different technologies, such as ultra-wide band (UWB) and WiFi fine-time measurement (FTM), in order to improve the performance of location. We also propose the use of fusion with cellular networks, such as LTE, to complement these technologies where the number of reference points is under-determined, increasing the availability of the location service. Maximum likelihood estimation (MLE) is presented to weight the different reference points to eliminate outliers, and several searching methods are presented and evaluated for the localisation algorithm. An experimental setup is used to validate the presented system, using UWB and WiFi FTM due to their incorporation in the latest flagship smartphones. It is shown that the use of multi-technology fusion in trilateration algorithm remarkably optimises the precise coverage area. In addition, it reduces the positioning error by over-determining the positioning problem. This technique reduces the costs of any network deployment oriented to location services, since a reduced number of reference points from each technology is required.

Keywords: indoor positioning; fusion technologies; UWB; WiFi fine time measurement; LTE; maximum likelihood estimator

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1. Introduction

Location-based services in the fifth generation (5G) mobile network require reliable, continuous, and precise positioning information for their full functionality potential [1]. Global navigation satellite systems (GNSS) have settled as the reference localisation system for outdoor navigation. GNSS offer a meter-level accuracy at open sky scenarios. However, the precision is reduced drastically when the target enters a building or tunnel. Several technologies (e.g., WiFi and Bluetooth) and techniques (e.g., fingerprinting and image recognition) try to provide accurate and precise location information [2,3]. Nevertheless, indoor scenarios are extremely challenging due to the harsh radio propagation conditions. Indoor scenarios usually contain metallic objects that reflect and block the signals creating multipath effects that can strongly deteriorate the navigation solution or create areas where no navigation information is available. Moreover, typical indoor scenarios are dynamic with constant changes due to the mobility of people within the scenario, such as in a shopping mall or an office. High-precision positioning becomes crucial for some Internet of Things (IoT) services, such as augmented reality (AR) or context-aware applications.

In recent years, some technologies have emerged for precise indoor localisation. There are two main families of techniques: based on trilateration, and based on fingerprinting. Trilateration consists in obtaining the position of the target based on the intersection of the distance between the target and at least three reference points. Some technologies that are being studied are ultra-wide band (UWB) [4], WiFi fine-time-measurement (FTM) [5] and cellular-based radio [1]. UWB has been widely adopted due to its robustness against multipath and its centimetre-level accuracy [6]. It may become the standard for indoor positioning in the next years as defined by ETSI [7]. Since UWB devices have a range of up to few tens of metres, they need a fairly dense deployment to ensure the required coverage. However, a dense deployment of UWB in the real world has a very high cost, making it feasible only for limited scenarios. WiFi FTM relies on the wide availability of WiFi access points (APs), and the higher range of WiFi signals to reduce the deployment costs, but it is still a fairly new technology that has not a wide commercial adoption. Although 5G ranging is still under research [8], it promises a very high availability thanks to the omnipresence of 5G base stations. Long term evolution (LTE) has also been used for obtaining location, although its precision is not as high as UWB or WiFi FTM [9].

WiFi fingerprinting [2,3] has also been widely studied. In fingerprinting, instead of using reference points, the terrain is divided in a lattice, and for each division, the set of visible WiFi APs is collected in an offline stage. For estimating location, a target will then obtain a list with the visible APs, and will use it to find the point in the lattice where it is most likely located. The map must be frequently updated to reflect changes in the environment.

In this work, we propose a method for opportunistically aggregating ranges obtained from different technologies. This fusion technique helps to reduce the cost of deployment because the end-user benefits from any nearby ranging reference point (RP) for localisation [10]. In addition, this technique also helps dealing with coverage holes of certain deployments, that is, areas where there are less than three visible reference points of one technology. Since not all ranges have the same precision, we propose a weighting stage that prioritises the reference points that offer a better location quality. To this end, this work uses a maximum likelihood estimator (MLE) to characterise the ranges and sources in order to define the weighting algorithm to balance the information of the over-determined system which provides high accuracy indoor positioning.

To validate the proposed method, we use a real location deployment with ranging information based on time measurement from UWB and WiFi and received signal strength from a LTE network as a back-up. To the best of our knowledge, no system unifies all these three technologies and brings them into a real scenario to show the performance of real-time localisation. We also test several search methods for the MLE, to compare the advantages in location precision and computational time of each one.

The contribution of this paper is listed as follows:

- Proposition of a fusion method in trilateration based on the work presented in [10], with a dynamic weighting with MLE that improves the robustness of location accuracy;
- Validation of the proposed method with a real-world setup with several different scenarios;
- Comparison between different MLE search methods for finding the best for resolving over-determined location problems.

The rest of this paper is organised as follows: Section 2 provides an overview of the different location technologies explaining features of the technologies used in this work. Section 3 explains the proposed method and the algorithm of multi-technology fusion and the MLE as a weighting technique for outliers. Section 4 describes the experimental setup with two scenarios and Section 5 presents the results obtained from three different cases deployed in the two scenarios. Section 6 discusses the results presented in the previous section. Finally, Section 7 presents the conclusions of this work.

The acronyms in this paper are listed in the Table 1 as follows:

Table 1. Overview of acronyms.

Acronym	Definition
5G	Fifth generation
AP	Access Points
AR	Augmented Reality
BLE	Bluetooth Low Energy
FCC	Federal Communication Commission
FTM	Fine-Time Measurement
GNSS	Global Navigation Satellite Systems
GPS	Global Satellite System
IoT	Internet of Things
L-BFGS	Limited-memory Broyden–Fletcher–Goldfarb–Shanno
LoS	Line of Sight
LTE	Long Term Evolution
NLoS	Non Line of Sight
MLE	Maximum Likelihood Estimator
PANS	Positioning And Networking Stack
RSSI	Received Signal Strength Indicator
RTT	Round-Trip Time
ToA	Time of Arrival
UE	User Equipment
UWB	Ultra-Wide Band
WLS	Weighted Least-Square

2. Overview of Location Technologies

The focus of the cellular-user location has changed over the generations from outdoors to indoors [1]. Thus, GNSS has had to adapt to the new requirements. However, other technologies and techniques have overcome satellite-ranging solutions for indoor positioning. Ranging-based or fingerprinting location have been studied [11,12] to provide a high accuracy for indoors with technologies presented in Table 2, such as Bluetooth or WiFi. Some of these technologies have been discarded for this work for several reasons. First of all, the scope of this work is to study the real-time positioning with technologies that do not need the data collection phase in fingerprinting, such as geomagnetism [12]. Secondly, user location must be computed in the cloud for two main reasons: it will help future applications, such as driver-less cars in which the cloud runs the commands to the cars and must know their positions [13], and computing in the cloud also helps reducing energy consumption in the end-device [14]. Thus, inertial navigation system (INS) is excluded for this study because it is unfeasible to send the information of the accelerometer or gyroscope in real time (update rate $\geq$ 100 Hz) with high energy efficiency. Thirdly, low-stability technologies, such as Bluetooth, might not allow to update in real-time, for the RSSI variations [15]. Moreover, Bluetooth provides an insufficient coverage for wide scenarios [16]. Hence, we decided to discard Bluetooth for this indoor positioning study. Henceforth, the technologies that are finally studied in depth for indoor positioning with high-precision performance are UWB and WiFi FTM. LTE is also studied as a back-up technology due to the wide-area coverage and deployed infrastructure. Table 2 presents an overview of the technologies mentioned in this study.

Table 2. Overview of indoor positioning technology.

Technology	Access Point	Positioning Accuracy	Positioning Method	Advantages	Disadvantages
Cellular network	Cellular tower	>30 m	Trilateration	World-wide coverage; No extra infrastructure needed	Low-precision >100 m
UWB	UWB anchor	cm-m	Trilateration	Robust against multpath; high-accuracy; easy-deployment	High-cost
WiFi-FTM	Router	cm-m	Trilateration	Low cost; high-accuracy	Not yet widely deployed
Bluetooth	Beacon	m	Trilateration; fingerprinting	Low cost; easy-deployment	Low-stability
INS	N/A	m	PDR	Self-sufficient	Accumulative error; Smartphone-based calculation
Geomagnetism	N/A	m	Fingerprinting	No infrastructure; low-cost; ubiquitous	Need data collection; affected by temporal electrical equipment;

Hereinafter, a brief description of cellular-based radio, UWB and WiFi that will be used in this paper is completed.

2.1. Cellular-Based Radio

Cellular-based localisation has been used as a simple and coarse solution when there is a lack of satellite visibility in GNSS, typically indoors and in scenarios, such as urban canyons [17]. The arrival of 5G brings new specifications for high-precision positioning as described in [9], which can be summarised in:

- Horizontal and vertical positioning error < 3 m for 80% of user equipments (UEs) in indoor deployments;
- Horizontal and vertical positioning error <10 m and <3 m, respectively, for 80% of UEs in outdoors deployments.

5G works on 700 MHz, 3.5 GHz and millimetre wave of 26 and 28 GHz. High frequencies allow high-precision ranging in direct line of sight (LoS) with the target but highly suffers from attenuation, multipath and reflections in non-line of sight (NLoS). In contrast, lower frequencies are more robust to attenuation reaching longer distances, however, multipath effects can deteriorate the precision of the ranges. In [1], in order to eliminate the need for clock synchronisation, the use of different timing techniques such round-trip time (RTT) are proposed for indoors.

Nevertheless, the existing and deployed LTE networks can be used as a back-up for other location technologies [10]. Despite of the coarse ranging information that LTE provides, LTE network is globally available in contrast with 5G that has not been yet fully deployed. End-users may benefit from LTE in cases where no high-precision technologies provide localisation. However, LTE utilises the received signal strength indicator (RSSI) for ranging. RSSI highly suffers from multipath and fadings which leads to high variations and an increase in the ranging error.

2.2. Ultra-Wide Band

UWB technology provides a high ranging accuracy based on the RTT protocol, even in environments with harsh propagation characteristics [18]. This technology has multiple advantages, such as centimetre-level ranging precision, good obstacle-penetration capabilities [4], and multipath mitigation in dense scenarios [2], making it indispensable for indoor positioning. UWB is also a wireless communication technology that supports a high throughput owing to the use of a very large spectrum. UWB uses very short time pulses of few nanoseconds that take a wide bandwidth. The Federal Communication Commission (FCC) authorised the unlicensed use of UWB in the range of 3.1 to 10.6 GHz [3]. UWB signals are centered at 3.5 GHz with a bandwidth higher than 500 MHz. The latest market trends show that UWB will soon become a de-facto standard for positioning and will eventually be addressed by 3GPP standards [7]. Accordingly, some smartphones have integrated UWB chipsets in the recent years [19]. As a drawback, to achieve the short pulse width the UWB device has a high energy consumption.

2.3. WiFi Fine Time Measurement

IEEE 802.11mc includes a fine time measurement (FTM) for range estimation in timing protocols using RTT [20,21]. This release will transform the indoor positioning industry in the next years because WiFi infrastructure is widely deployed. The protocol estimates precisely the distance to any WiFi access point (AP) which supports the protocol without needing to be connected to them [22]. The information is calculated on the device for privacy preserving, since sensitive location information is not shared among network peers. In [23], the accuracy for positioning of WiFi FTM is computed with a precision of a meter-level accuracy in real scenarios with dense deployments of WiFi APs.

3. Materials and Methods

3.1. Proposed Positioning Method

In trilateration, the position of the target is in the intersection between geometric forms, such as circles or hyperbolas defined by the distance between the target and the RP [1–3]. Any ranging information can be used to obtain the final target position, such as time of arrival (ToA), RSSI, or RTT time measurements. A minimum of three sets of reference points and ranges to each one is required for location in 2D. The proposed algorithm is explained in Algorithm 1. First, once the ranging information is received, the MLE weights each source depending on whether the source is new or the system already has information about it. Then, the trilateration algorithm based on the weighted least-square (WLS) algorithm is computed [24]. Once the position is obtained, the algorithm computes the error based on the distance provided by the source and the computed position. Finally, this error is temporarily stored and the weighting factor of the source is updated for the next iteration. In this section, both techniques that will be used in this paper are described: multi-technology fusion and maximum likelihood estimation (MLE).

Algorithm 1: Positioning algorithm with MLE and fusing technologies

```
Input: Distance and position from reference points.
foreach Reference Point do
    if Reference Point is new: then
        Assign a low initial weight.
    else
        Weight the reference point according to the accuracy of the last
          measurements.
    end
end
Compute the position of the target by WLS algorithm.
Estimate the distance from the target position to each reference point.
Calculate the error between the input and the estimated distances.
Storage temporarily the error of each reference point.
Output: Position of the target.
```

For a better understanding, we have also provided a flowchart of the proposed positioning method that will help to understand how the whole system works in Figure 1.

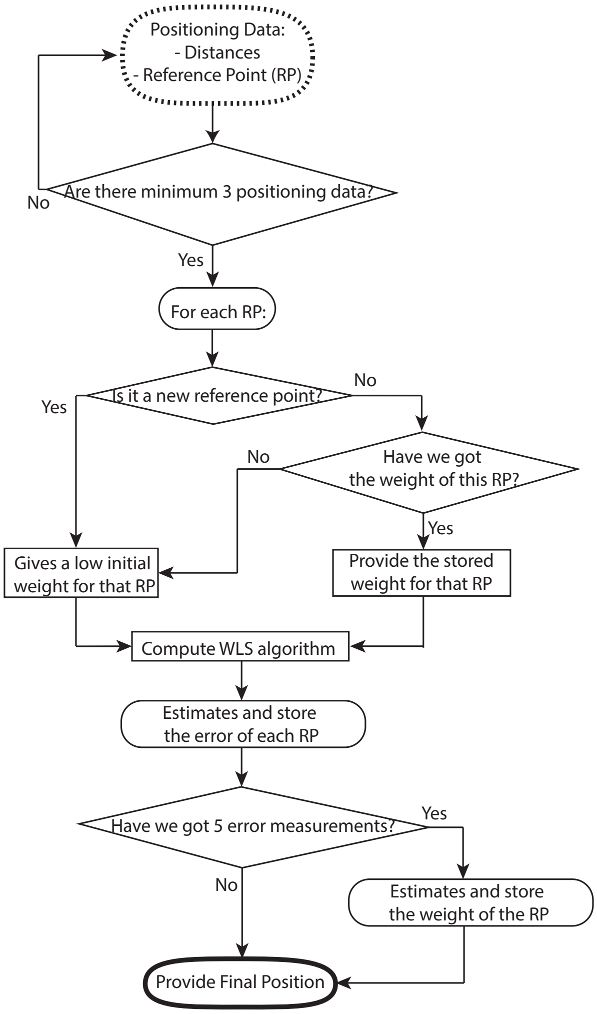

Figure 1. Flowchart of the system.

3.2. Multi-Technology Fusion

In trilateration the ranging information usually comes from a single technology. However, in [10], a scheme for fusing ranges from different technologies is presented. The use of multi-technology fusion in trilateration improves low-precision accuracy provided by technologies (in this work, LTE) by using the ranges of precise technologies, such as UWB or WiFi FTM.

In addition, to enhance the end-user location precision, multi-technology fusion also provides a seamless navigation between areas served by different technologies (e.g., exteriors where GNSS can be used, and interiors with UWB deployments, using other ranging technologies, such as LTE to cover for the missing ranges in the borders). Fusion benefits from high-precision reference points in a sparse deployment which can help to improve location in emergency cases, such as fires, earthquakes, etc. In these scenarios, fusion can also compensate the missing AP structures with portable APs in order to provide high-precision localisation. Although in this paper we have set the focus on WiFi FTM and UWB for precise positioning, other technologies which provide high-precision ranging data could also be used, such as GNSS or Bluetooth.

3.3. Maximum Likelihood Estimator (MLE)

Ranging information is uncertain because measurements are never ideal. Least squares (LS) estimation solves over-determined systems even though they are inconsistent since it is not possible to find a solution. The idea is to find a solution which minimises the error of the system. However, the classical iterative LS method for positioning lacks robustness; even a single outlier can introduce a great error in the estimated target position. This problem increases when the final accuracy should be reduced to the sub-meter accuracy. In [10], WLS was used to compute the location with trilateration, but to avoid the problem of outliers, the ranges were weighted according to their precision. A higher weight was assigned to UWB (which is more precise) than LTE. However, these weights were assigned statically; so, if a specific device introduced a high-precision ranging error (due to factors such as an especially challenging location for propagation, or software and hardware malfunctions), the localisation accuracy would be considerably affected.

Maximum likelihood estimator (MLE) is the most popular estimator for obtaining the parameter $\hat{\theta}$, which specifies a probability function $P(X = x|\theta)$ or a probability density function $p(X = x|\theta)$ of a discrete or a continuous variable based on the observations $x_1, x_2; \ldots, x_n$ which are independently sampled from the distribution [25]. In this work, MLE weights the ranges provided by different reference points in real-time depending on the variation of the error attached to the ranges. The system stores the error associated to each RP iteratively with a temporal window and weights the sources by their standard deviation. Supposing that $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$ with distribution $F_{\boldsymbol{\theta}}$ being $\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_n\}$ that follows the density function $f_{\boldsymbol{\theta}}(x)$ [26]. Hence, the likelihood function of the observation is given by:

$$L(\boldsymbol{\theta}; \mathbf{X}) = \prod_{i=1}^{n} f_{\boldsymbol{\theta}}(X_i) \tag{1}$$

The MLE estimates the best candidate that optimally maximises L as seen below:

$$\hat{\boldsymbol{\theta}} = argmax(log(L(\boldsymbol{\theta}; \mathbf{X}))) \tag{2}$$

Hence, assuming that observations follow a Gaussian distribution, the estimator calculates the parameters of mean and standard deviation that best suits Equation (2). In this work, MLE dynamically weights the different reference points at the WLS algorithm. Once the target's position is estimated, the distances ($\hat{\mathbf{d}}_{\mathbf{est}} = \{d_{est1}, d_{est2}, \ldots, d_{estn}\}$) from the estimated position to each RP positions are calculated. Then, the estimated error of each RP ($\hat{\mathbf{e}}_{\mathbf{est}} = \{e_{est1}, e_{est2}, \ldots, e_{estn}\}$) between the estimated distances ($\hat{\mathbf{d}}_{\mathbf{est}}$) and the input distances (initially for the LS algorithm) are obtained. Finally, MLE provides the weight values of each RP based on the error ($\hat{\mathbf{e}}_{\mathbf{est}}$) from the last N time epochs. The value of N depends on the periodicity that the measurements are captured. We store the N elements that were captured in the last 5 s. Figure 2 represents the weighted values of different reference points during an experiment. In this case, it can be observed that a WiFi AP is overweighted for some epochs. Then, owing to a blocking of line of sight between the target and the WiFi AP, the weight of the WiFi AP is reduced drastically due to the precision of the range being reduced to the level of lower precision technologies such as LTE base stations (BSs).

Thus, the system benefits from the most stable and precise ranges. When the MLE receives a new input source (i.e., a new RP and its distance), the estimator assigns a low weight during the first N epochs in order to check the stability of the new source. In case a RP data are not captured, the MLE erases the stored data of that RP. Once all the information is weighted, WLS algorithm utilises the weights to provide the best target position. To find the solution, several searching techniques can be used for the MLE:

- Nelder–Mead: is the most widely used algorithm in direct search method for solving the unconstrained optimisation problem. The Nelder–Mead method iteratively generates a sequence of tetrahedrons to approach the optimal point which can reflect, expand, contract, and shrink. The algorithm is designed for small search spaces because it quickly stalls [27];

- Limited-memory Broyden–Fletcher–Goldfarb–Shanno (L-BFGS): is designed for large non-linear optimisation problems. The algorithm handles bounds on the variables and solves unconstrained problems. However, the convergence is slow and non-optimal for real time cases [28];
- Truncated Newton (TNC): utilises rougher estimations of the optimal search direction for efficiency. As a drawback, the algorithm appears to rapidly stall [29];
- Constrained optimisation by linear approximation (COBYLA): is a direct search method which only incorporates linear models about the objective and the constrains with quick searching time [30];
- Sequential least squares programming (SLSQP): is an iterative method in which the objective and constraints functions demand to be triple continuously differentiable. The method reduces the non-linear optimisation problems by sequential iterations to trim the convergence time [31].

In this paper, the SciPy [32] package implementation of these algorithms was used.

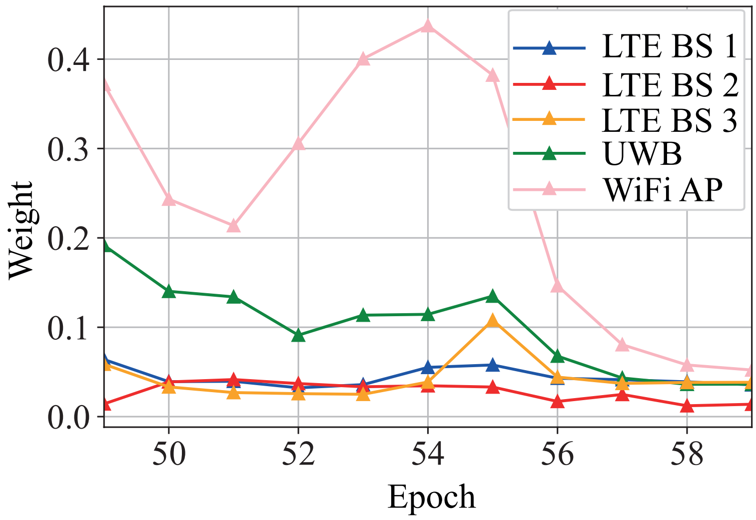

Figure 2. Functionality of the MLE during a real experiment.

4. Experimental Setup

In this section, an experimental setup for validating the solution is described. To validate the benefits of the proposed solution with real data, an UWB and a WiFi FTM deployment are used as high-precision ranging technologies and an indoors LTE network as a backup element with low-location accuracy and high availability. LTE is used as a placeholder of 5G due to the lack of an experimental infrastructure, but the conclusions of the experiment are expected to be similar with femtocells in a height of 3.5 m. The LTE network belongs to the University of Malaga which has configured the network to reduce the interferences with commercial networks. On the other hand, according to the multipath effects, the scenario is a laboratory which presents several metallic elements, such as computers, shelves, etc. Therefore, we expect that the measurements are heavily affected by multipath. The UWB deployment is based on Decawave DWM1000 devices (DecaWave, Dublin, Ireland) and they were placed on top of shelves in order to cover the whole scenario with good visibility (2 m height). Meanwhile, the WiFi FTM APs are Google WiFi mesh routers (Google, Montain View, CA, USA) that were placed in typical places for providing WiFi connectivity throughout the laboratories (1 m height). Both DWM1001 and Google WiFi routers are set to their default configuration parameters [33,34]. The UWB devices transmit with a power of -14.3 dBm and they are centered in 6 GHz [34]. The Google WiFi routers are configured to work at 2.4 GHz and, to the best of our knowledge, the WiFi

RTT FTM function could not operate at 5 GHz. The transmission power of the router is by default 28.17 dBm [33]. The LTE station parameters are configured with a transmission power of −6.8 dBm and downlink and uplink frequencies of 2630 MHz and 2510 MHz, respectively. The location target device is a Google Pixel 3 which runs Android 9.0 and supports WiFi FTM RTT. An application has been programmed to capture all the ranging data from the network reference points: LTE base stations, UWB anchors and WiFi APs. The ranges with the LTE stations are estimated using the measured RSSI which is modelled by the indoor office propagation model [35]. The WiFi FTM ranges are obtained from an API created for this work. For the UWB measurements, a DWM1000 device is attached to the smartphone and connected via Bluetooth low energy (BLE) to read the UWB data. A limitation on the performance of the UWB devices is that the UWB tag can only receive the information of four anchors simultaneously due to the software provided with the DWM1000 family products [4]. The implementation of the positioning and networking stack (PANS) firmware, the two-way ranging (TWR) communication protocol and the data frame limit the number of anchors that the tag can listen at the same time. Hence, despite a high-density set-up, the system is not highly over-determined. The captured data are sent to a Flask server with a MySQL database which is configured in a laptop(Lenovo, Beijing, China) running Windows 10. The sampling rate is 1 Hz. The measurements are timestamped with the global satellite system (GPS) clock as a time reference. The measurements are captured in a reduced time interval, assuming simultaneous samples which would introduce some error due to synchronisation. However, a regular user moves slowly in indoor scenarios which can lead to a maximum error of a few centimetres of ranging information. Additionally, we have set the height of the phone to 1.1 m of height simulating a person is carrying the phone on his pocket. Then, we send the information to the Flask server to process the localisation data via HTTP with no retransmission allowed in order to maintain the experiments as real-time.

These experiments were performed in three laboratories and hallways with a very limited vision of the sky. Figure 3 illustrates the three experimental cases that have been measured in the two different scenarios. These cases were selected in order to demonstrate the advantages of fusing technologies and the performance of the MLE and its different searching methods for localisation. Two experimental cases were carried out as shown in the high-density deployed scenario illustrated in Figure 3a. In Case 1, seven regular UWB anchors (in green) and three Google WiFi devices are used to show the performance of fusion with high-accuracy ranges. The numbers of UWB and WiFi devices were chosen in order to fully cover the scenario with at least three anchors or AP ranging data in the whole area. In Case 2, two UWB anchors in bad locations (in red wine colour) were added to the Case 1. In this scenario, UWB and WiFi will complement their information and improve the geometry of the problem by having the reference points more evenly distributed. Thus, with multi-technology fusion in trilateration the problem becomes over-determined for each point, and it also has more reference points distributed over a wider area (which means that the coverage of the overall system increases). As opposed to the scenario shown in Figure 3a, Figure 3b shows a realistic scenario with one regular UWB device, one WiFi AP and three LTE base stations distributed on the laboratories. With this deployment, the high-precision information availability is reduced to a small area. LTE is used in order to augment the availability of the positioning service. Nonetheless, with this deployment, a high precision can only be achieved when there are three high-precision reference points in range. When LTE is used, a low precision location is provided, which is still better than a full outage in location provision.

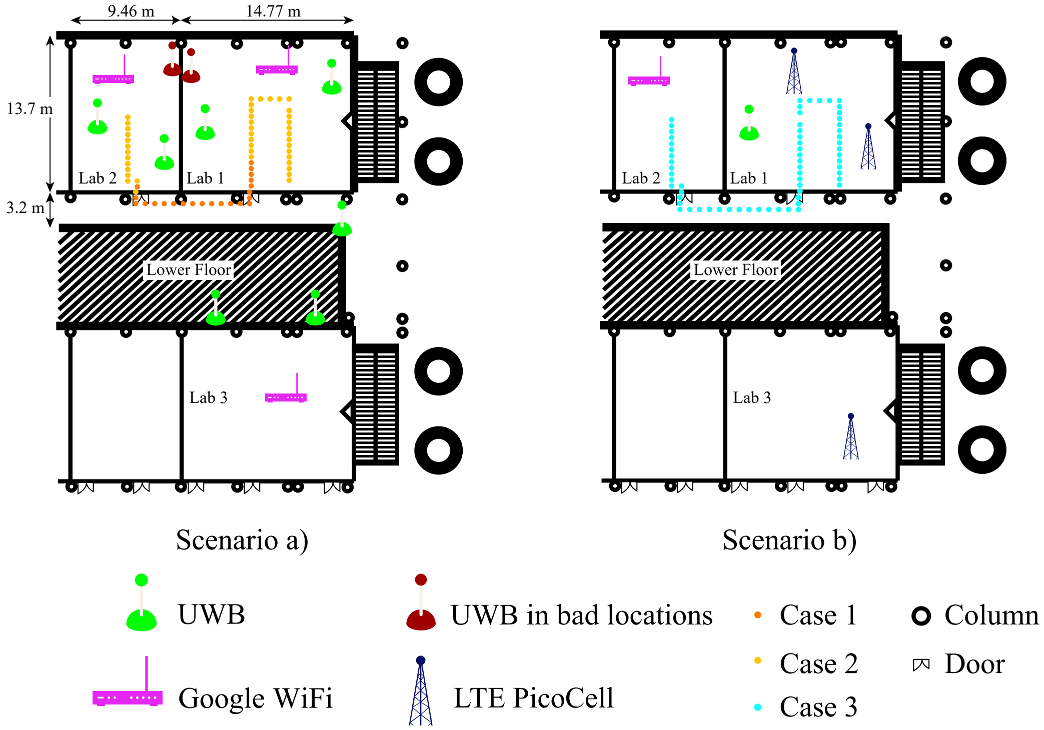

Figure 3. High density (**a**) and low density (**b**) scenario set-up distribution.

5. Results

In this section, the results obtained from each case are described separately in order to demonstrate the performance of multi-technology fusion. Moreover, the different searching methods of MLE are executed in order to observe some location characteristics for each Case.

5.1. Results from Multi-Technology Fusion

5.1.1. Case 1: High-Density Deployment with Good UWB Conditions

In this first experiment, the set-up represents a scenario with a high-density of UWB reference points, such that at any point the visibility of at least four anchors is guaranteed. Moreover, all the anchors are in a location with good propagation conditions, favouring a low ranging error. Figure 3a represents the scenario, with the UWB anchors and the captured location data for one trajectory (yellow and orange dots). Figure 4 shows in 2D the performance of system with the estimated locations (blue dots) against the ground truth points (yellow dots). The UWB (green diamonds) and WiFi (pink triangles) illustrate where the devices are placed. Figure 5 shows the location accuracy achieved with UWB, WiFi FTM and the fusion of both in this case compared with the ground truth. In Figure 5, fusion median (yellow line), standard deviation (rectangle height), and outliers (circles) improves significantly from UWB and WiFi isolated cases. UWB localisation is better than WiFi in this case. Despite having UWB anchors in good conditions, the positioning error has an average near one meter. This meter-level accuracy is due to multipath effects that affect both UWB and WiFi FTM (which has a lower accuracy). When using fusion, the accuracy improves, with a lower average and much lower variance.

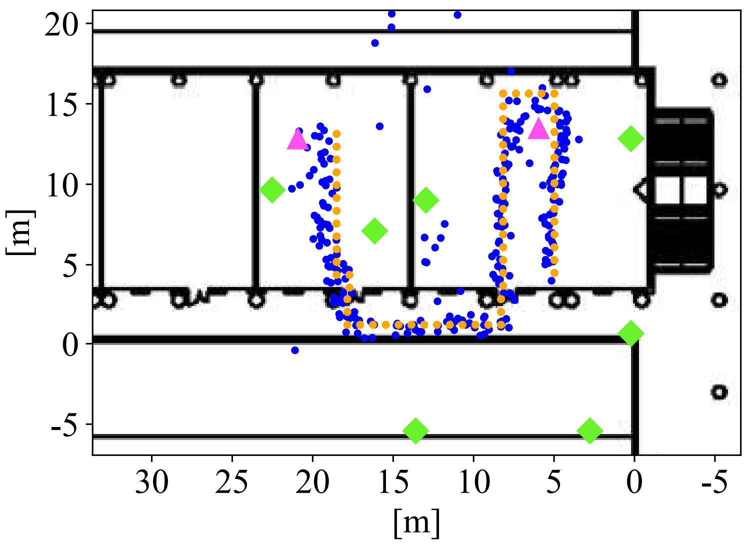

Figure 4. Localisation performance of Case 1 in 2D.

5.1.2. Case 2: High-Density Deployment with 2 UWB in Bad Locations

As in the previous case, the set-up ensures the positioning service provided by UWB with the ranging information of four anchor most of the time. However, in this case, two of the anchors are installed in locations where a partial blocking of the anchors leads to bad propagation conditions due to NLoS. This situation can be common in the real world, where quick deployments are completed for situations such as emergencies or temporary events. The bad deployment causes these anchors to report ranges with a higher error. The data captured for this case are illustrated in Figure 3a as yellow dots. In this case, the error of the only-UWB location service is much larger than in the previous case as shown in Figure 5. Again, fusion median and standard deviation improve against isolated technology localisation.

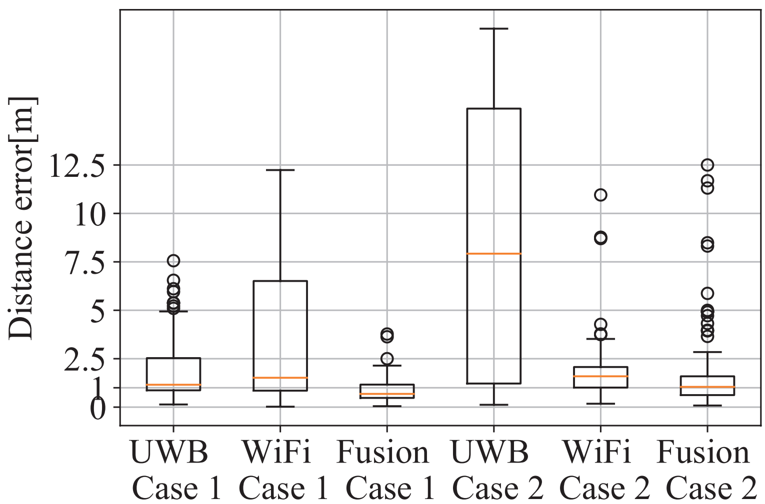

Figure 5. Horizontal error distribution of UWB + WiFi FTM for Cases 1 and 2.

A cumulative density function (CDF) of the error is given to illustrate and compare the performance of Cases 1 and 2 as shown in Figure 6. The pink horizontal line represents 90% sample line, and the error for using fusion in Case 1 drastically improves the horizontal error. However, the outliers introduced by UWB in Case 2 have worsened the fusion performance and WiFi, in this case, locates better the user in isolation.

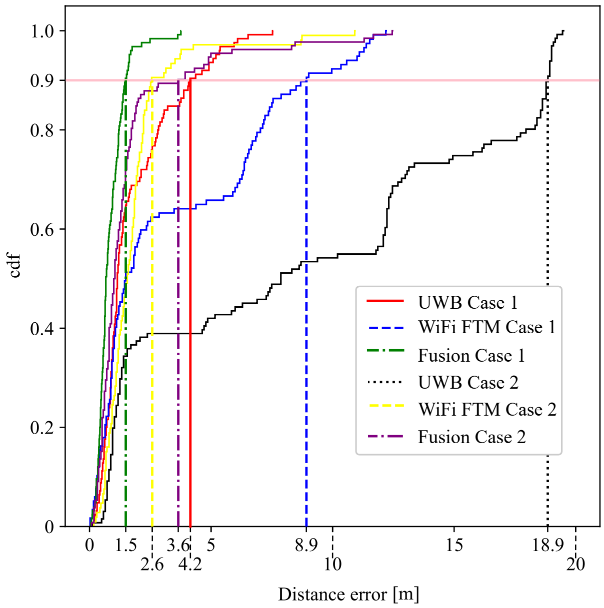

Figure 6. CDF of the horizontal error for Case 1 and 2.

5.1.3. Case 3: Low-Density Deployment of High-Precision Technologies

In this third case, the scenario is set up as a more realistic situation with less dense high-precision devices than in the other Cases. In this case, the low-density of devices in the scenario makes it impossible to locate a target by using the high-precision information from UWB and WiFi devices, since the visibility of at least four reference points is not guaranteed. Therefore, in this case, the missing ranges are complemented with LTE ranges, which are less accurate. Figure 3b represents, in light blue dots, the positions where the location service is provided by using the LTE data. In Figure 7, there is a comparison of the location error between the only LTE and multi-technology fusion between LTE with UWB anchors and WiFi AP ranging information.

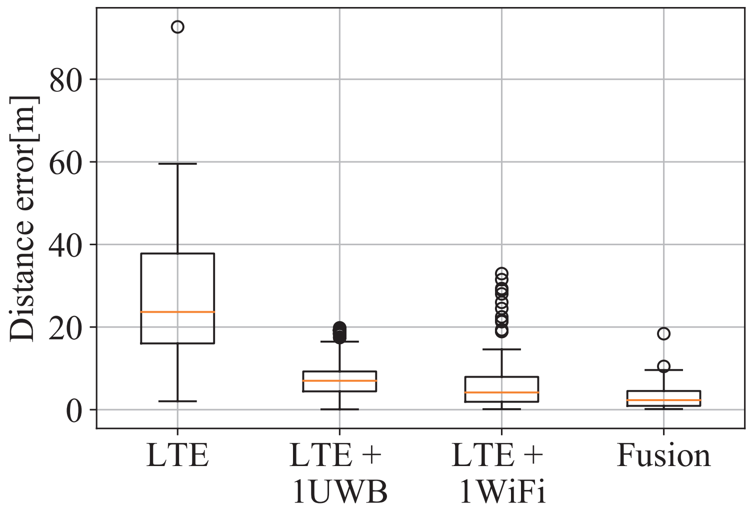

Figure 7. Horizontal error distribution of LTE and fusion for Case 3.

In addition, the CDF of Case 3 has been also included when using fusion with 1 UWB anchor, 1 WiFi AP or LTE plus both technologies as shown in Figure 8. In this Case, precise ranging information greatly enhances the localisation accuracy of the multi-technology system.

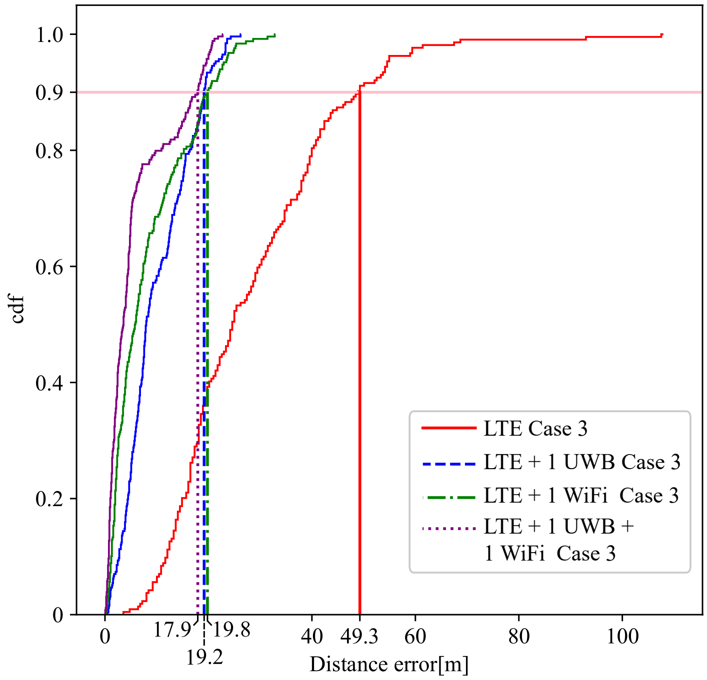

Figure 8. CDF of the horizontal error for Case 3.

Comparing Figure 9 (imported from [10]) with Figure 8, the fusion algorithm stands out in both works showing the benefits of using high-precision data in areas only covered by low-precision ranging technology such as LTE. In Case 3, just as in the simulation of [10], LTE provides a worse precision performance when it is used in isolation. There is a contrast between the results obtained in this work and in [10] because in the simulation the case of the study was ideal in which some real-world conditions such as reflections, clutters, and interferences, were omitted.

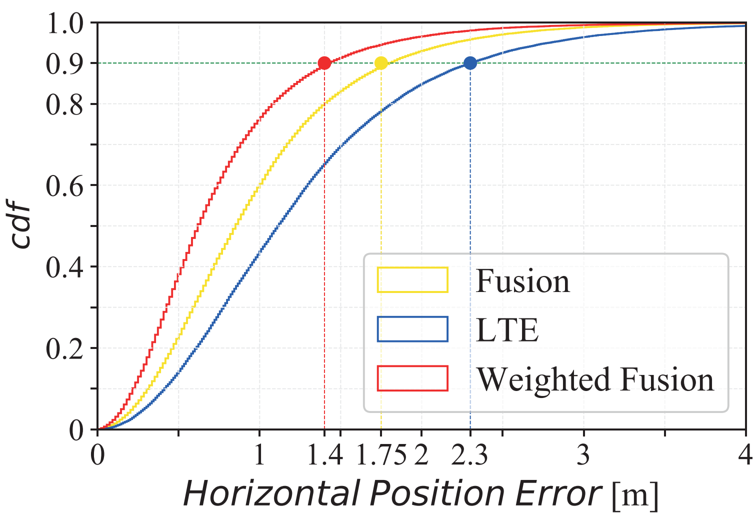

Figure 9. Horizontal Position Error of LTE (blue), fusion (yellow) and weighted fusion (red).

5.2. Comparison of the MLE Searching Methods for Positioning

Searching methods may provide different solutions to weight the sources. Nelder–Mead, COBYLA, and SLSQP are linear methods which may perform better for estimating the standard deviation of the sources. In addition, L-BFGS-B is designed for large problems and TNC provides a rougher estimate to achieve a faster converge. Thus, L-BFGS-B and TNC may perform a priori worse than the rest. In this Section, a comparison of the performance of the different searching methods for the MLE are shown in Table 3 in the three different cases. All the results are obtained by using multi-technology fusion in trilateration. In addition, the different searching methods are compared with a non-weighted LS solution to show the performance of the MLE in positioning problems. Table 3 shows the mean (μ), standard deviation (σ), the 80% of the cumulative error (CDF) in meters and the time elapsed for each iteration in milliseconds.

Table 3. Comparison of the search methods in both scenario.

		Nelder-Mead	L-BFGS-B	TNC	COBYLA	SLSQP	No Weighting
Case 1	μ [m]	1.14	1.46	1.43	1.14	1.14	1.07
	σ [m]	0.77	1.2	0.99	0.77	0.77	0.67
	80% cdf error [m]	1.63	1.84	1.93	1.63	1.63	1.45
	Time elapsed [s]	0.103	0.065	0.169	0.200	0.067	0.070
Case 2	μ [m]	0.98	1.52	1.52	0.96	0.95	1.11
	σ [m]	0.67	1.74	1.74	0.67	0.67	0.84
	80% cdf error [m]	1.3	1.83	1.83	1.25	1.23	1.46
	Time elapsed [s]	0.125	0.079	0.176	0.225	0.082	0.078
Case 3	μ [m]	18.7	19.08	18.36	18.7	18.7	18.14
	σ [m]	9.65	10.75	10.14	9.66	9.66	10.71
	80% cdf error [m]	27.84	27.36	26.88	27.84	27.84	25.71
	Time elapsed [s]	0.109	0.059	0.194	0.254	0.052	0.050

6. Discussion

In this section, the results are discussed showing the advantages of using multi-technology fusion. Moreover, the results obtained for the different searching methods are reviewed providing a guideline on which is the most convenient.

6.1. Performance of Multi-Technology Fusion

As seen in the previous section on Figures 5 and 7, the error obtained by multi-technology fusion improves substantially with respect to single-technology positioning performance. With fusion, more measurements over-determine the WLS algorithm and also the geometry of the reference points enhances from a denser deployment. The over-determination of the localisation problem might not enhance the system performance with the inclusion of MLE if a RP appear intermittently, in which case MLE drastically reduces the impact of this intermittent RP.

On the other hand, the combination of isolated high-precision ranging technology with low-precision technology such as LTE shows a considerable improvement in all the possible aspects, such as mean, standard deviation, or the magnitude of the outliers, as seen in Figure 7. Despite LTE being a coarse precision ranging technology, it fills the lack of ranging information to solve the WLS algorithm for location augmenting the coverage area where location is provided. Therefore, taking advantage of the fact that several technologies are already deployed in the measurement scenario (and also in many real-world situations), the multi-technology fusion technique can be used to exploit different deployments, improving accuracy, coverage, and reducing the cost of new deployments.

6.2. MLE Search Methods

Regarding the MLE algorithm, it does not improve the target location performance overall when all the devices are in good visibility and propagation conditions (such as Case 1), instead, it slightly worsens the positioning error, as seen in Table 2. This is because MLE assigns a low initial score to the new sources. Nevertheless, the benefits of MLE appear in more realistic scenarios where input data introduces outliers (Cases 2 and 3).

In Case 2, the use of MLE, with the methods of Nelder–Mead, COBYLA or SLSPQ, improve the location system performance in all the statistical metrics proposed in the Table 2 and SLSQP has a very similar time resolution without using MLE. In Case 3, it is noticeable that the MLE reduces the standard deviation error, although it increases the mean error. This is expected due to MLE reducing the impact of data with higher variances. Thus, despite reducing the impact of the standard deviation, the offsets introduced by multipath predominate on the location estimation. Again, the SLSQP search method is very similar to the non-weighted method. Hence, L-BSGS-B and TNC both show not to be suitable for positioning. In contrast, SLSQP search method proves better than the rest of the methods for improving the location performance against outliers or bad propagation conditions that are very typical for indoors scenarios.

The positive results obtained with MLE can be further improved using techniques, such as Kalman filters [24], or complementing the weight calculations with additional contextual information, such as the knowledge of LOS/NLOS conditions (obtained, for instance, with machine learning) [36].

7. Conclusions

In this work, the main objective is to present multi-technology fusion with MLE as a weighting algorithm in a real scenario. Thanks to the fusion technique, the presence of multiple technologies can be used to improve location in diverse ways: with a higher precision and with a higher availability. When the number of high-precision reference points is high, fusion provides an over-determination that allows a higher precision. In cases where the number of high-precision reference points is low (for instance, in the border of deployments, or in sparse deployments), multi-technology fusion allows using low-precision and highly available technologies, such as LTE, to complement the reference points and do trilateration to achieve a high availability on the localisation service.

Moreover, the proposed technique does not need any additional hardware apart from the receivers for each technology that will be present in most mobile devices in the near future. Thus, fusion allows to reduce costs in positioning infrastructure deployments due to a lower density requirement of high-precision devices.

To validate the weighting technique with MLE, tests with real deployments were completed in three different Cases. MLE is presented in this paper as a technique that reduced the impact of outliers for precise positioning. Only in ideal cases with very good condition deployments, the error slightly increases. SLSQP stands out as the best search method for MLE in positioning problems.

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sensors

Article

WiFi FTM and UWB Characterization for Localization in Construction Sites

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Abstract: A high-precision location is becoming a necessity in the future Industry 4.0 applications that will come up in the near future. However, the construction sector remains particularly obsolete in the adoption of Industry 4.0 applications. In this work, we study the accuracy and penetration capacity of two technologies that are expected to deal with future high-precision location services, such as ultra-wide band (UWB) and WiFi fine time measurement (FTM). For this, a measurement campaign has been performed in a construction environment, where UWB and WiFi-FTM setups have been deployed. The performance of UWB and WiFi-FTM have been compared with a prior set of indoors measurements. UWB seems to provide better ranging estimation in LOS conditions but it seems cancelled by reinforcement concrete for propagation and WiFi is able to take advantage of holes in the structure to provide location services. Moreover, the impact of fusion of location technologies has been assessed to measure the potential improvements in the construction scenario.

Keywords: WiFi FTM; UWB; position control; location fusion; indoor positioning

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1. Introduction

In recent decades, a new industrial revolution has emerged thanks to the introduction of Information and Communication Technologies (ICTs) in industrial processes [1], giving place to the Industry 4.0 paradigm. However, the construction sector remains particularly obsolete in technology adoption compared to other sectors, such as manufacturing [2,3]. The main activity of the construction sector takes place on the construction site, which is a highly changing environment, the vast majority of which is outdoors, and usually involves different actors, such as different companies and a large number of workers during the different stages of the project. Moreover, the use of heavy machinery, such as cranes or trucks, and harmful or heavy materials also come into play, which make these scenarios dangerous and whose monitoring and safety tasks are often difficult to fulfill. In this context, new ICTs are emerging that allow location and monitoring of the different resources, as well as the automation of tasks or the remote control of some elements, help to achieve a more efficient and safer construction environment [4].

In Industry 4.0, advances in the fields of robotics, AI, and Machine Learning (ML) come together to conform production to new customer demands, such as an increased customization, optimal machinery efficiency, and reduced costs [5]. Thus, the whole industry is advancing towards more flexible and adaptable scenarios through wireless environments. Wireless networks allow flexibility, scalability, and mobility that can be translated into real-world applications in the construction sector, such as remote driving [6], autonomous cranes [7], or real-time workers location and health monitoring [4].

Technological progress in recent years has focused its efforts, among other objectives, on the location of users. The Global Navigation Satellite System (GNSS) has established itself as the reference location system for outdoor navigation [8]. However, in more hostile scenarios for signal reception, such as indoor scenarios or scenarios surrounded by metallic elements, such as construction sites, it has not been successful. These types of scenarios often contain metallic objects that reflect and block signals, create multipath effects that deteriorate target location accuracy, or can create areas with coverage holes. In addition, typical construction scenarios are dynamic with constant changes due to the different phases the project goes through. Therefore, a location that meets the requirements of reliability, continuity, and accuracy for location-dependent applications, such as Augmented Reality, or Autonomous Robots, is a major challenge [9].

This paper evaluates and compares the performance of ultra-wide band (UWB), WiFi fine time measurement (FTM) and fusion of technologies in a construction scenario with an indoor scenario from a previous work [10]. This evaluation is backed by measurements taken in a real construction site, where UWB and WiFi-FTM setups were deployed. The measurement campaign included samples from several different floors in an incomplete building. The measurements are used to assess the precision of each technology individually. In addition, an algorithm [11] to opportunistically fuse the ranges obtained from different location technologies is studied. This fusion technique helps to reduce the deployment cost by reusing elements from different technologies as reference points, which may be deployed for other purposes in the construction site [10]. In locations with a high density of reference points (RPs), the system to be solved is overdetermined, i.e., it has extra information to improve its accuracy. Since all the RPs provide different accuracies, we include a weighting step that prioritises the RP that provides a better ranging accuracy [11]. In addition, the fusion technique also deals with coverage holes of certain deployments, for example, in areas where there are less than three visible RPs of a technology, fusion takes advantage of the information of other technologies to be able to offer the location service. To the best of our knowledge, there are no papers studying the precision of location systems in construction sites and that compared them with the precision of an indoor scenario. As novel ICTs emerge in the construction industry, these studies will become a necessity to properly select the location technologies for such applications.

The rest of this paper is organized as follows: Section 2 gives an overview of the different location technologies explaining the characteristics of the technologies used in this work. Section 3 explains the proposed method and the trilateration fusion algorithm. Section 4 describes the experimental setup of the scenario. In Section 5, the results obtained in the deployed scenario are presented and discussed. Finally, Section 6 presents the conclusions of this work.

2. Overview of Location Technologies

This section provides an overview of the two location technologies that are most commonly used indoors, and may therefore be used in construction scenarios.

2.1. Ultra-Wide Band (UWB)

UWB provides high distance measurement accuracy based on the Round Trip Time (RTT) protocol, even in environments with difficult propagation characteristics [12]. This technology has multiple advantages, such as centimeter-level accuracy, good obstacle penetration capability [13] and multipath mitigation in dense scenarios [14], making it indispensable for positioning in complex scenarios. UWB is also used as a wireless communication technology that supports high throughput due to the use of a very wide spectrum. UWB uses very short time pulses of a few nanoseconds that occupy a wide bandwidth. UWB signals are centered on 6.5 GHz with a bandwidth greater than 500 MHz. The latest market trends show that UWB may soon become a de-facto standard (albeit this prediction is recently being challenged by IEEE 802.11 mc). Therefore, some smartphones have already integrated UWB chips in recent years. The main drawback is that, in order to achieve a short pulse width, the UWB device has a high power consumption for a single packet transmission [15,16]. Thus, using the RTT protocol, which needs the exchange of multiple packets, will increment the energy consumption.

2.2. WiFi Fine Time Measurement

The IEEE 802.11mc standard includes precise fine time measurement (FTM) for distance estimation to the router by time stamping using the RTT protocol [17,18]. This version will transform the indoor positioning industry in the coming years as WiFi infrastructure and connectivity is widely adopted. The protocol accurately estimates the distance of any user supporting the WiFi FTM protocol without the need to be connected to the router [19]. The information is calculated on the device to preserve privacy, as sensitive location information is not shared between network nodes. In [18,20], the accuracy for WiFi FTM positioning is estimated to be around one meter in real-world scenarios with dense deployments of WiFi routers or access points (APs).

3. Location Computation

Although fingerprinting claims to provide high accuracy with low infrastructure deployment, it has some drawbacks that make it unfeasible for the construction case. First, it requires complex training that makes it impractical to cover the entire infrastructure. Secondly, the periodicity of this training becomes very frequent due to constant changes in the environment. Thus, the trilateration method seeks to find the final position of the user through the intersection between geometric shapes, such as circles or hyperbolas defined by the distance between the target and the different RPs [14,21,22].

Although the received power may not follow a specific propagation model, if the environment does not change drastically, it tends to remain static over time.

Since the distances contain errors in the measurements due to different factors, such as reflections or blockages, these distances do not intersect at a point but generate an area of uncertainty which is where the solution to the problem lies. Therefore, the Weighted Least Square (WLS) iterative method finds the optimal solution to this problem as follows:

$$\begin{aligned} A &= \begin{pmatrix} \frac{x^n - bs_{x_0}}{\rho_0} & \frac{x^n - bs_{x_1}}{\rho_1} & \dots & \frac{x^n - bs_{x_n}}{\rho_n} \\ \frac{y^n - bs_{y_0}}{\rho_0} & \frac{y^n - bs_{y_1}}{\rho_1} & \dots & \frac{y^n - bs_{y_n}}{\rho_n} \end{pmatrix} \\ \mathbf{y} &= \mathbf{p}^n - \mathbf{p} \\ \Delta\mathbf{p} &= (A^\top W A)^{-1} A^\top W \mathbf{y} \\ \mathbf{p} &= \mathbf{p}^n + \Delta\mathbf{p} \end{aligned} \tag{1}$$

where A is the Euclidean distance matrix of the computed position ($\mathbf{p}^n$) which is defined as $p(x,y)$ in the n iteration, ρ_i is the pseudodistance from the target to the i reference point and $bs_i(x,y)$ is the coordinate of the reference point in the second dimension. W is the weighted matrix and ($\mathbf{bs}_i$) are the coordinates of the different RPs. The innovation vector $\mathbf{y}$ computes the difference between the estimated and the initial position $\mathbf{p}$ which is updated until the variation $\Delta\mathbf{p}$ does not exceed an arbitrary threshold.

In trilateration, it is usually assumed that the distance measurement information comes from a single technology. However, in [11] a scheme for merging ranges from different technologies is presented. Moreover, in [10] the UWB and WiFi FTM technologies are presented in a real indoors scenario where the result of locating users using these two technologies separately and in fusion is shown. In the present work, the same algorithm is presented to compare the performance of the different technologies in different scenarios. The use of fusion in trilateration improves the accuracy of the final estimated location. In addition, fusion in trilateration also provides seamless navigation between areas served by different technologies (e.g., outdoors where GNSS can be used, and indoors with WiFi deployments, using other distance measurement technologies to cover missing ranges at the borders). Fusion leverage signals from isolated high-accuracy landmarks or that are part of incomplete deployments, such as in situations where a dense deployment is not possible, such as in stages of a construction where the addition of walls has caused blockages, the removal of scaffolding has reduced the mounting points for RPs or even in occasions where part of the infrastructure has been destroyed (e.g., fires, earthquakes, etc.). In these scenarios, fusion can compensate for missing RPs with portable APs to provide high-precision location.

The classical Least-Square algorithm is highly influenced by outliers. However, the Maximum Likelihood Estimator (MLE) estimator evaluates signal accuracies to enhance the location service. MLE obtains the parameter $\hat{\theta}$ which determines a probability density function $p(X = x|\theta)$ of a continuous variable based on $x_1, x_2; \ldots, x_n$ which are independent observations of the distribution [23]. In this work, MLE weights the ranging information obtained by different RPs depending on the error of the ranges compared with the final solution to insert this information in the WLS with the W matrix. The system stores the error of each RP iteratively with a temporal window and weights the sources according to their standard deviation. Supposing that $\mathbf{X} = \{X_1, X_2, \ldots, X_n\}$ with distribution $F_{\boldsymbol{\theta}}$ being $\boldsymbol{\theta} = \{\theta_1, \theta_2, \ldots, \theta_n\}$ that follows the density function $f_{\boldsymbol{\theta}}(x)$ [24]. So, the likelihood function of the observation is given by:

$$L(\boldsymbol{\theta}; \mathbf{X}) = \prod_{i=1}^{n} f_{\boldsymbol{\theta}}(X_i) \tag{2}$$

The MLE estimates the best candidate that optimally maximizes L as seen below:

$$\hat{\boldsymbol{\theta}} = argmax(log(L(\boldsymbol{\theta}; \mathbf{X}))) \tag{3}$$

Assuming that observations follow a Gaussian distribution [18,25,26], the estimator calculates the parameters of mean and standard deviation that best suits Equation (3). Thus, the given observation vector to the MLE follows a normal distribution, as indicated in [8], which provides the optimal value. In this work, MLE obtains the weights of the different RPs based on the error from the last N time epochs which may improve over-determined location systems.

4. Experimental Environment

In this section, an experimental setup for evaluating UWB, WiFi-FTM, and fusion in a real construction scenario is described. To show the performance of the different technologies with real data, a setup of UWB anchors and a WiFi FTM APs has been deployed. In this work, two experiments have been performed to evaluate the ranging and location accuracy in the same floor of UWB, WiFi and fusion, and to evaluate the penetration capacity and accuracy of UWB and WiFi in different floors (one above and below from where the deployment is set-up). The first experiment takes place in the basement floor -1 during the construction phase of a building site, as can be seen in Figure 1. In this floor, the view of the sky is completely cancelled, making unfeasible the use of GNSS. The construction site was at a stage where the structure of the floors was built although the walls had not yet been built as shown in Figure 1a. Figure 1b shows the steel bars inside the reinforcement concrete that act as Faraday cage for the signal propagation. This structure is present in the walls, floors, ceiling, and columns. Thus, the second experiment evaluates the penetration capabilities of UWB and WiFi. Figure 1c shows how the anchors are attached to the walls for the measurement campaign. Duct tape was used in order to avoid interfering with the construction works, and taking into account that it does not affect the propagation of wireless signals. This deployment strategy was also drawn in conjunction with the construction company, which provided guidance on typical practices and material limitations of the environment. Specifically, this approach was recommended due to its low cost, low intrusiveness, and high flexibility.

(**a**) (**b**) (**c**)

Figure 1. Pictures of the scenario: general view (**a**), structure of the floor and ceiling (**b**) and setup of an UWB anchor (**c**).

In the first experiment, the distribution of the UWB anchors and WiFi APs are represented in Figure 2 as blue and red triangles and indicated as UWB or WiFi *X*, respectively. The yellow dots represent the ground truth of the path there and back where the measurements are taken. In this experiment, all the measurements were taken in LOS conditions and for UWB4 and UWB6 in partially NLOS conditions. Two path there and back measurement recollections were performed to have a sufficient dataset, over 150 samples that were collected statically during each 30s measurement. UWB anchors are set at different heights (indicated in Figure 2) and the WiFi APs are placed on the floor to avoid falls. In the second experiment, the green boxes (1, 2, and 3) show the positions used to measure the penetration capabilities of UWB and WiFi one floor above and below of each point. In this experiment, we evaluate the penetration capabilities, i.e., the number of packets that can reach the UE, and the ranging accuracy of how it degrades from LOS to a NLOS scenario. In the positions marked by the green boxes, the UWB and WiFi devices are placed together on the floor (height = 0m). The measurement campaign at each point was of 5 min with an update date of 3 Hz.

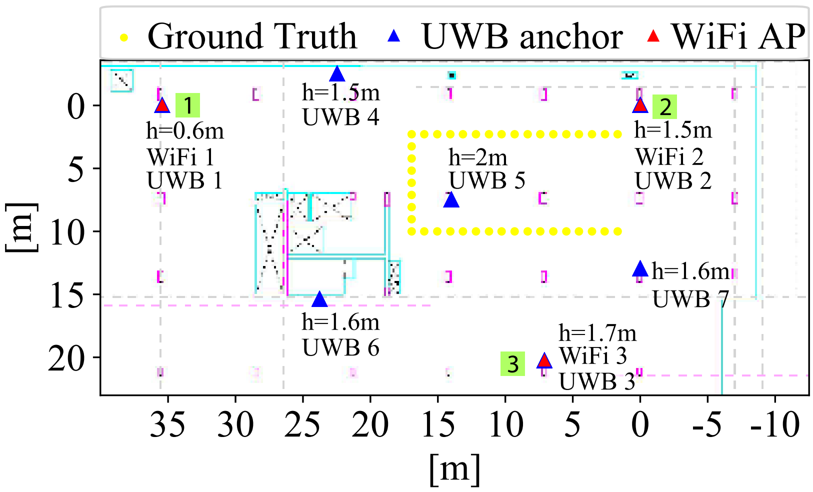

Figure 2. Scenario with UWB and WiFi technologies.

A Google Pixel 3 acts as the location target. This smartphone runs Android 9.0 and supports WiFi FTM RTT. An application has been programmed to collect all distance measurement data from the RPs seen by the terminal: anchors for UWB and APs for WiFi.

However, Google Pixel 3 does not support UWB technology yet. Thus, an UWB device is attached to the smartphone (acting as a tag, i.e., location target) and connected via Bluetooth Low Energy (BLE) to the smartphone which reads the UWB data. The developed application relays the captured data via WiFi to a server where it is stored and processed. The database is a Flask server with a MySQL database that is configured on a Windows 10 laptop. Samples have been collected in an offline phase to check the accuracy of the positioning results with a sampling rate of 0.3 Hz.

The UWB devices—anchors (reference points) and tag (location target)—are based on Decawave DWM1001 devices which compute the range estimation via RTT protocol [27]. The UWB devices transmit with a power of −14.3 dBm and they are centered in 6.5 GHz [27]. One limitation in the performance of these UWB devices is that the tag can only receive information from four anchors simultaneously due to the default firmware that DWM1001 devices have installed [13]. Thus, despite of the high density of UWB anchors, the positioning algorithm with UWB only will use up to four anchors that does not exploit the full environment information. The WiFi APs are Google WiFi routers which are configured to work at 5GHz to support the WiFi FTM RTT protocol [28]. Additionally, different bandwidth gives different precision as indicated in [29]. For ranging estimations at 90% CDF error, it is expected to have the following tolerances: 80 MHz (2 m), 40 MHz (4 m), and 20 MHz (8 m).

5. Results

This section describes the results obtained in each experiment to demonstrate the performance of the different technologies for positioning accuracy and penetration capacity.

5.1. Accuracy of UWB and WiFi in the Same Floor

Figure 3 shows the cumulative density function of the horizontal error (x–y axes) as a result of trilateration obtained with UWB, WiFi, and fusion using trilateration. It also compares the performance with the indoor scenario (Case 1) presented in [10].

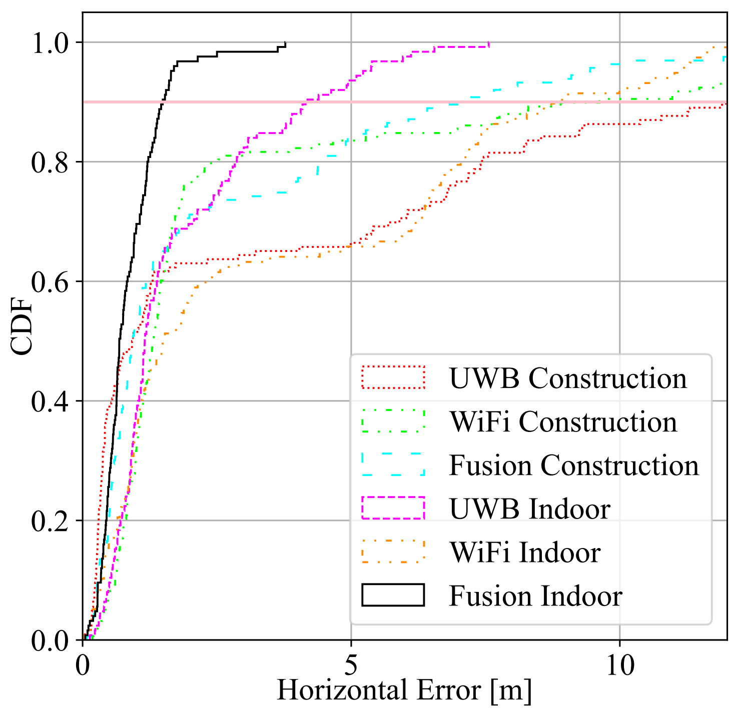

Figure 3. CDF Horizontal error distribution of UWB, WiFi FTM, and fusion in the construction site and in a indoor scenario.

Table 1 displays the relevant statistical parameters of the first location experiment, i.e., the mean, standard deviation of the error, and the 2σ parameter (95% of the sorted error) compared with the ground truth in UWB, WiFi, and fusion in both scenarios, construction site and laboratory, as a result of the trilateration with MLE algorithm.

Table 1. Comparison of the horizontal error between UWB, WiFi FTM, and fusion in the construction site and indoor.

	Mean [m]	**Standard Deviation [m]**	**90% of Error [m]**
UWB Construction	3.69	4.70	13.51
UWB Indoor	1.82	1.54	5.22
WiFi Construction	3.02	4.45	14.14
WiFi Indoor	3.53	3.55	11.11
Fusion Construction	2.40	3.05	9.41
Fusion Indoor	0.86	0.58	1.65

In addition, Figures 4 and 5 represent the ECDF of the ranging accuracy of the different UWB and WiFi devices to the target during the measurement campaign in LOS and partially in NLOS (mainly for UWB4 and UWB6) conditions.

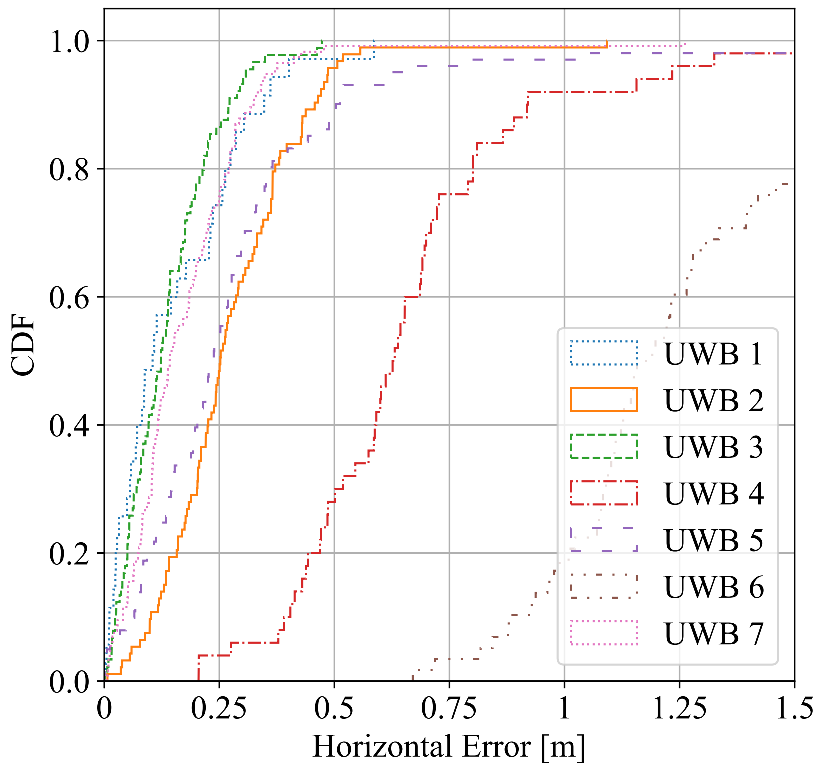

Figure 4. UWB ranging estimation error in LOS conditions.

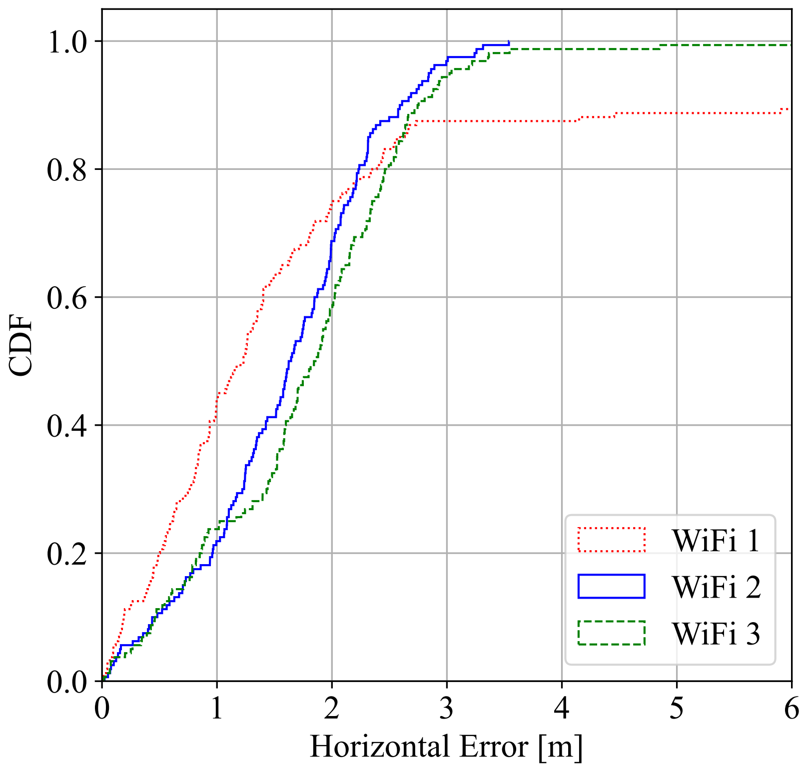

Figure 5. WiFi ranging estimation error in LOS conditions.

As can be observed, UWB seems to perform better than WiFi for ranging accuracy and, therefore, in location estimation. In general terms, the geometry of the deployment and features of the environment (e.g., construction site with LOS/NLOS, reinforced concrete walls and floors, etc.) are key factors that may change the performance of a location system. Indoor scenario ranging outperforms compared to the construction site, and the fusion algorithm enhances both UWB and WiFi performance in both scenarios. Despite having all UWB anchors and WiFi APs located in areas with good propagation conditions, the 90% percentile of the positioning error is above a meter in all construction cases due to multipath effects, geometry distribution, which leads to dilute the final precision, that affects both UWB and WiFi FTM although, for WiFi, it can be seen that the effects are slightly smaller. Despite having worse ranging performance in WiFi, the final solution is similar to the UWB final results. As it can be seen, more ranging information in fusion improves the geometry of the system and overdetermines the LS algorithm, which results in a better performance. In this case, the fusion algorithm benefits from the data of estimated ranges to RPs obtained from multiple technologies (normally 7 ranging data), when UWB only captures normally 4 ranging data and WiFi a maximum of 3 ranging data. The full potential of fusion is realized in cases where the scenario is such that RPs of a single technology do not offer full coverage. In other words, in scenarios where points where less than 3 RPs of a single technology are visible. In these cases, fusion may complement the missing RPs with a different technology. Nevertheless, in the setup of this experiment, our objective was not to demonstrate this opportunistic nature of fusion.

5.2. Penetration Capacity and Accuracy of UWB and WiFi in Another Floor

In this second experiment, we measured the location provided by the RPs one floor above and below the scenario. The first observation was that no signal was received from UWB. In other words, to have location in a floor, the UWB anchors must be installed in the same floor. Figure 6 shows the percentage of the packet loss of the RTT packets at the different points (1, 2, and 3) on the lower (Floor −2) and upper (Floor 0) floors of WiFi. These loss rates reflect a reliability that could be sufficient for non-critical applications; for instance, worker tracking or tool location which normally require update rates of a few Hz [30]. Half of the measurement points (Below 1 at Floor −2, Above and Below 3 at Floors 0 and −2, respectively) show a much higher loss rate due to the reinforcement concrete which block the signal. In one of the measurement points (Above 3 at Floor 0), no packets were recorded at all. In contrast, in the other half of the measurements (Above 1 at Floor 0, Above and Below 2 at Floors 0 and −2, respectively), the RPs can communicate with the smartphone due to some holes present in the structure of the building among different floors that are shown in Figure 7a–c.

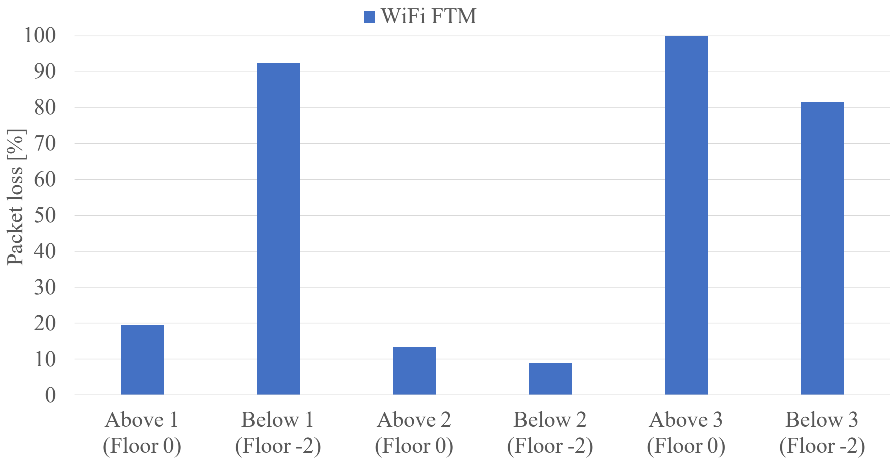

Figure 6. Percentage of WiFi coverage on the floor above and below the measurements taken.

(**a**) (**b**) (**c**)

Figure 7. Images of the connection between floors.

Figure 8 shows the ranging error (i.e., the error in the distance measured to the WiFi-FTM RP) for each of the measured points. It can be seen that the Above 2 at Floor 0 and Below 3 at Floor −2 are the most precise points, despite having high packet losses. In the points with lower packet losses, precision is slightly lower and there is a higher tendency for outliers. This is due to the impact of the holes in the building structure; while they help propagation, they also introduce a higher error due to multipath. The error maintains below 5 m of ranging error, despite the fact that in some cases the packet rate loss exceed the 80% of the transmitted packets. This means that in cases where only signal penetration is available for positioning, the ranging error maintains stability in general.

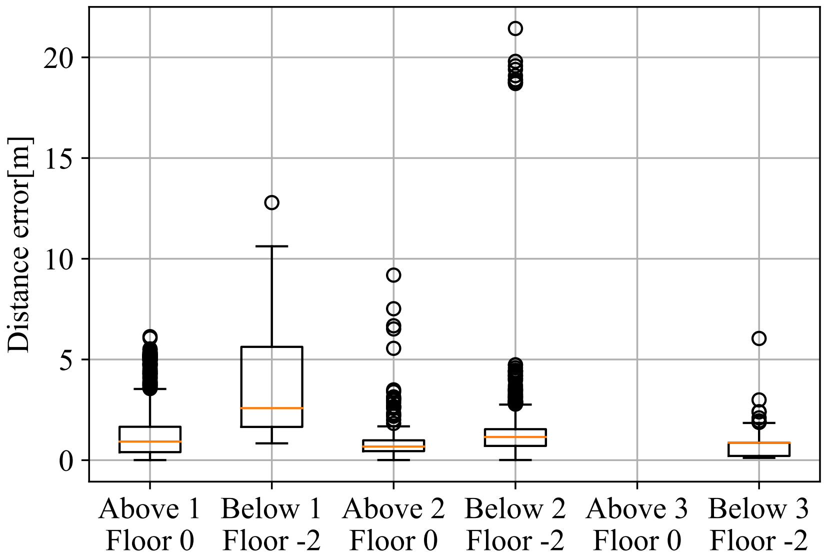

Figure 8. WiFi error on the floor above and below measurement.

As it can be observed, the error estimation reasonably increments compared with performance of the WiFi ranging information in LOS conditions from the first experiment in Figure 5.

6. Conclusions

This paper presents the results of a measurement campaign of UWB and WiFi FTM in a construction scenario for location purposes. The goal of the experiments is to compare the accuracy, coverage, and penetration capability of UWB and WiFi technologies and the fusion of technologies in this type of dynamic scenarios. UWB has demonstrated to provide better ranging accuracy, however, WiFi has demonstrated robustness against blocks in the scenarios with better propagation performance and penetration capabilities. The measurements show the elements of the construction site affect in UWB and WiFi ranging estimation compared with an indoor scenario. Moreover, it can be observed that fusion can improve the accuracy of location in all scenarios.

Penetration measurements show that reinforcement concrete completely cancels UWB propagation and WiFi is able to benefit from holes in the structure to achieve location. However, in cases where no holes are present, WiFi performs with difficulties for positioning, but still manages to report ranges.

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Abbreviations

The following abbreviations are used in this manuscript:

AP	Access Points
BLE	Bluetooth Low Energy
FTM	Fine-Time Measurement
GNSS	Global Navigation Satellite Systems
ICT	Information and Communication Technologies
ML	Machine Learning
MLE	Maximum Likelihood Estimator
RP	Reference Point
RTT	Round-Trip Time
UWB	Ultra-Wide Band
WLS	Weighted Least-Square

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Digital Object Identifier

Evaluation and Comparison of 5G, WiFi and fusion with incomplete maps for Indoor Localization

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ABSTRACT Precise positioning will play a key role in future 5G/6G services. The upcoming location-based services drive the necessity of high-precision positioning to indoors. In fingerprinting, which is the most commonly used location algorithm indoors, comprehensive radio maps are essential for a precise localization service and highly influence on the result of the final position of the user. A Machine Learning (ML) algorithm that supports missing information from the map may improve the robustness and reliability of the localization service. In this work, we compare the performance of the classical fingerprinting technique and different Decision Tree Regressor (DTR) -based algorithms that are Decision Tree Adaboost (DTA), Linear Tree Adaboost (LTA) and Random Forest (RF). The experiments were carried out with real 5G and WiFi data in an indoor scenario to test the performance of the techniques. Additionally, we demonstrate the benefits of fusion of technologies when positioning with radio maps. Finally, an evaluation of the robustness from the different methods was carried out when missing information in the training phase.

INDEX TERMS Fingerprinting, Adaboost, Random Forest, 5G, WiFi, Fusion, Indoor localization.

I. INTRODUCTION

As an increasing number of customer services rely on location to satisfy the needs of both users and network operators, Localization-as-a-Service (LaaS) is becoming increasingly vital for 5G and 6G networks [1]. LaaS is critical in enabling new location-based services such as autonomous robots and vehicles [2], smart education [3] or e-Health [4]. The 3GPP has set a target of achieving high localization accuracy for 5G networks, aiming for submeter accuracy in certain cases such as autonomous driving, where location accuracy below 10 cm is envisioned [5], and an accuracy of below 3 meters in most cases (both indoors and outdoors) [6]. Combining context-aware data from the Internet of Things (IoT) collected through WiFi networks with 5G information can enhance the accuracy, reliability, and scalability of localization services [7], [8].

Accurate location estimation has become increasingly important in recent years, and the use of Global Navigation Satellite Systems (GNSS) is a common approach for achieving high accuracy in outdoor environments. However, issues like signal blocking, attenuation, and multipath effects make GNSS ineffective indoors, where many applications are being developed. To address this, supplementary technologies like 5G, WiFi, or Ultra Wide Band (UWB) are often used to determine location [9], [10]. In situations where energy constraints on user devices require network-based location to conserve battery and optimize computational efficiency, the network estimates the User Equipment (UE) location based on data collected in the network infrastructure in a non-cooperative manner [11]. Some applications, such as beam management or automatic configuration of network parameters, may also require terminals to transmit their location using specific protocols [12], which can be complex and energy-intensive. An alternative solution to determining location is through network-based location [13]. This method involves the network utilizing data collected from the network infrastructure in a non-cooperative manner to estimate the location of a terminal.

Cellular networks like Long Term Evolution (LTE) are commonly used to locate users when GNSS is unavailable [14]. The most common approaches are location by proximity, ranging-based methods, Angle of Arrival (AoA) and fingerprinting. Location by proximity is the easiest method to determine the location of the UE because it assumes the location of the gNodeB (gNB) is the location of the UE and is used when high accuracy is not required [15]. Ranging-based methods, such as trilateration, involves using ranges obtained through methods such as Received Signal Strength Indicator (RSSI) or Time of Flight (ToF) [9] and can be very accurate if ranges are precise. The determination of the location involves estimating the interception of 4 spheres (or 3 in 2D location). Nevertheless, range estimations are not normally accurate, occasionally resulting in the non-convergence of circles or hyperbolas utilized in the trilateration process. To solve the uncertainty, techniques such as Least Squares (LS) or Weighted Least Squares (WLS) are used [16]. AoA measures the angle at which the signal reaches the UE from the gNB. Multiple Input Multiple Output (MIMO) systems are capable of transmitting with beamforming that can be used to implement the AoA approach [17]. Indoor environments pose reliability challenges for both range-based models and AoA due to the susceptibility of the models to signal blocking and reflections. While the received power might not follow a predetermined propagation model, in cases where the environmental conditions remain relatively stable, it is observed to remain constant over time. For instance, if we consider a location in close proximity to a WiFi AP and the measured power is unusually diminished due to an obstacle such as a wall, this power level will remain unaltered over time as long as the obstruction remains stationary. As a result, each point in space is associated with a set of paired values comprising reference point identifiers and unvarying received power levels. This principle underlies the concept of fingerprinting, these paired values conform a distinctive signature, commonly referred to as a *fingerprint*, which serves to uniquely identify each point in space [18].

Fingerprinting exhibits several primary drawbacks. It notably demonstrates high sensitivity to disparities between training and testing conditions arising from dynamic propagation attributes such as temperature, humidity, and obstacles [19]–[21]. Additionally, it mandates an extensive preliminary map construction phase, which necessitates thoroughness [22]. This is imperative because unrecorded data points remain unusable for positioning during the operational phase. Lastly, the integrity of the radio map is compromised due to device heterogeneity stemming from variations in orientation and chip sensitivity [23].

Fingerprinting has some disadvantages, which include the requirement for a long map-building phase in advance. This process must also be comprehensive because unmeasured points cannot be used for location in the exploitation phase. Other studies have explored the reconstruction of maps containing missing data. In [24], they addressed this issue by leveraging the linear nature of signal propagation. Their objective was to recover missing data by considering the context of the existing map, allowing for the application of techniques like fingerprinting. It is important to note that this approach is constrained by the granularity of the radio map division, which directly impacts the final accuracy of the system. When the division is finer, precision increases, but it also necessitates a larger number of minimum required data points. Another avenue explored is the utilization of Deep Learning techniques for the recovery of missing data points from maps. However, it is observed that this approach has limitations and can only recover up to 50% of the missing data [25].

Supplementary techniques such as combining ranging with AoA can enhance the final location estimation of a UE, resulting in a higher degree of accuracy [9], [26]. The fusion of multiple technologies helps to increase the density of reference points in the scenario, providing more information for the final estimation stage. This reduces the cost of infrastructure or expands the coverage area [27].

The contributions of this paper are listed as follows:

- Implementation of fingerprinting and model-based algorithms utilizing real 5G and WiFi data.
- Evaluation of the performance of positioning systems when fusing different technologies employing map- and model-based methodologies.
- Examination of the the behavior of the algorithms when varying different percentages of missing data in the training phase.
- Proposition of model-based techniques for a percentage of missing data points over 50% while minimizing the degradation on the localization performance.

The rest of the paper is organized as follows. Section II explains both the fingerprinting algorithm and various DTR-based techniques. Section III provides an overview of benefits of fusion of technologies. In Section IV, the experimental setup and the scenario are described. Section V analyzes the results of the outcomes that were obtained from the data collection campaign and the implementation of various location methods with different experiments. Finally, Section VI presents the conclusions of this work.

The acronyms in this paper are listed in the Table 1 as follows:

II. LOCATION TECHNIQUES

In indoor environments, techniques like trilateration can be challenging due to the possibility of signal blocking and reflections, which can result in significant errors. ToF based ranging estimation can reduce these errors, but it can be expensive due to the hardware requirements [9]. In indoor environments, however, there are typically multiple radio signals that can be measured and reported without hardware modifications. In cellular networks, UEs are required to measure all visible base stations and report this information to the serving base station to determine the best cell [28]. In stable indoor environments, the received power tends to remain constant, making radio map techniques particularly useful.

TABLE 1: Overview of acronyms

Acronym	Definition
Adaboost	Adapting Boosting
AoA	Angle of Arrival
AP	Access Point
CDF	Cumulative Distribution Function
DTA	Decision Tree Adaboost
DTR	Decision Tree Regressor
IoT	Internet of Things
gNB	gNodeB
GNSS	Global Navigation Satellite Systems
LaaS	Localization-as-a-Service
LTA	Linear Tree Adaboost
LTE	Long Term Evolution
MIMO	Multiple Input Multiple Output
ML	Machine Learning
RF	Random Forest
RMSE	Root Mean Square Error
RSSI	Received Signal Strength Indicator
ToF	Time of Flight
UE	User Equipment
UWB	Ultra Wide Band
WL	Weak Learner

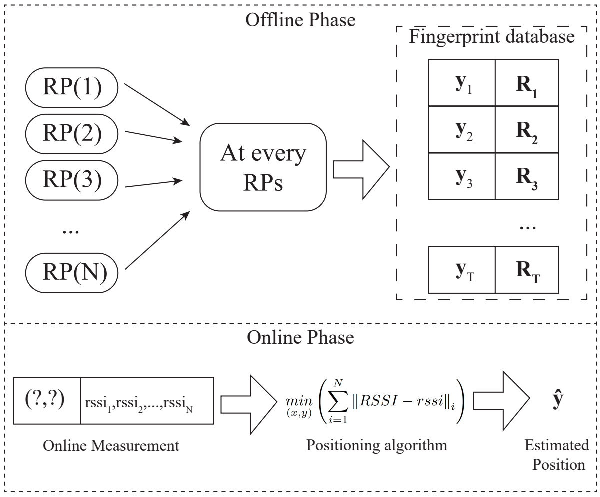

FIGURE 1: Fingerprinting method

This section will provide an overview of various techniques suitable for these types of scenarios.

A. FINGERPRINTING

Classical fingerprinting is a localization technique that involves generating a unique *fingerprint* of wireless signal strength and other characteristics of a particular location. This *fingerprint* can be later used to identify the location of a device. The process of creating a *fingerprint* involves measuring wireless signal characteristics at various points within an area, such as a building or campus. In static environments where changes are minimal, the received power at a specific point in space remains relatively constant over time. As a result, each point $\boldsymbol{y_i}$ can be represented in a database of T entries using a vector that contains the RSSI measurements of the N nearest APs with known positions in WiFi and gNBs in 5G networks, $\boldsymbol{R} = (RSSI_1, RSSI_2, ..., RSSI_N)$, as shown in Figure 1. Consequently, each point has a distinctive RSSI vector that constitutes its *fingerprint* allowing for accurate location tracking.

Fingerprinting involves two distinct phases, as illustrated in Figure 1. The first phase, known as the offline or training phase, involves creating a radio map by assigning a unique *fingerprint* to each point on a regular grid. In the second phase, called the online or exploitation phase, the terminal measures the surrounding gNBs and generates a new vector $(rssi_1, rssi_2, ..., rssi_N)$. This vector is then compared to the different points on the map to find the most similar *fingerprint*. To determine the most probable position $\hat{\boldsymbol{y}}$ on the grid, the algorithm seeks the point that minimizes the Euclidean distance between the new vector of RSSI and the *fingerprint* database, as described in the positioning algorithm equation shown in Figure 1.

The level of accuracy in the fingerprinting method depends on several factors such as the size of the grid used during the training phase, the variance of the measured power for each component, and the accuracy of the UE's measurements. There is a tradeoff between complexity and accuracy; this is crucial because using a smaller grid results in a shorter training phase but with lower accuracy, while a finer grid requires a longer training phase but with higher accuracy.

WiFi and cellular networks are commonly associated with fingerprinting due to the high density of stations in office and residential areas [18], [29]. Fingerprinting can provide high accuracy with a reduced infrastructure investment, but it requires the creation of a radio map with a complex training phase. To maintain location precision, the maps need to be updated when there are changes in the environment. Furthermore, the maps must be comprehensive, meaning that all points on the grid must be systematically measured in order to properly locate users at any point.

B. DTR-BASED LOCATION

Fingerprinting has a major drawback in that it requires complete information about the environment, without any missing data. To address this issue, a commonly used approach is to employ ML algorithms to create an environment model [30]–[32], which can then be utilized for estimating the position during the exploitation phase. ML algorithms generate a comprehensive model of the scenario through the information provided in the training phase with certain reference points. Consequently, even without conducting measurements across the entirety of the scenario during the training phase, the ML model enables a localization service encompassing the entire designated area [33], [34]. In the context of a grid scenario with missing data, this study utilized DTRs, which are recognized for their simplicity and computational efficiency [35], to estimate the position.

By creating a set of hierarchical comparison rules that are applied sequentially, DTRs model the behavior of the localization system. The resulting path over a tree is determined by the outcome of each rule (branch), leading to a final node (leaf) that decides the output of the regressor as illustrated in Figure 2.

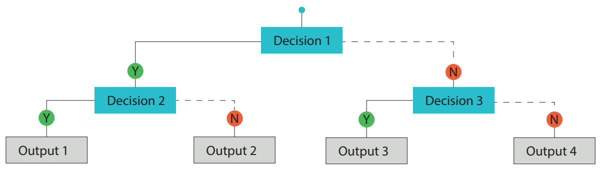

FIGURE 2: DTR functionality

The DTR learning process comprises two phases: training and testing. In the training phase, the 80% of the available samples are randomly selected to form the training dataset D_{train}, while the remaining 20% of the dataset D_{test} is used for testing. The objective of the training phase is to create a tree that minimizes the regression error on the training set.

In this work, we study different DTR-based algoritms that were chosen due to its high accuracy and low complexity: Random Forest (RF) and two Adaboost-based training algorithms that are Decision Tree Adaboost (DTA) and Linear Tree Adaboost (LTA). DTA, in its final prediction of positions, combines outputs from different WLs by using a decision rule and taking their average [36]. On the other hand, LTA creates an interpolation function by taking into account the different outputs of a set of decision rules [37], [38].

1) Random Forests

RFs are a ML technique that employs a collection of individual models (known as *base models*) to generate a final prediction. This ensemble method is versatile and can be applied to various ML tasks such as classification, regression, or localization. RFs are especially useful for localization tasks because they can effectively aggregate the predictions of multiple decision trees to determine the location of a device [39], [40].

RFs employ the bootstrapping method to generate decision trees, which involves a random subset of the training data that is selected to create a single decision tree. This process is repeated several times, leading to a vast number of decision trees trained on various subsets of the data. To generate the final prediction of the localization process, the predictions of all the decision trees in the forest are averaged as depicted in Figure 3.

The implementation of RFs is relatively straightforward, as they utilize decision trees, which makes them computationally efficient. Additionally, RFs are resistant to data noise since average of all the location outputs mitigates the impact of any individual decision tree that might produce an inaccurate estimation.

Algorithm 1 explains with pseudocode the structure and formulation of the RF algorithm [41]. Given T samples and N features (in this case, APs) labeled $([\boldsymbol{R}(1), \boldsymbol{y_1}], ..., [\boldsymbol{R}(T), \boldsymbol{y_T}])$ where the input vector is a tuple compound by a RSSI vector formed by $RSSI_n(t)$ from the nth AP and tth sample and the localization output $\boldsymbol{y_t}$ that is

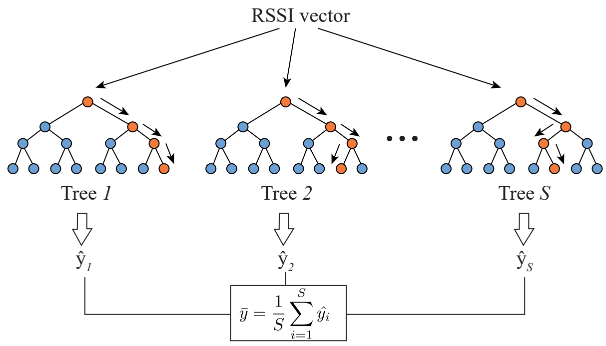

FIGURE 3: RF schema

the final position of the user in a 2D plane. For training the RF, we generate S trees as an arbitrary number of the size of the forest. On each iteration $i = 1, ..., S$, we select a random subset of features ($\boldsymbol{S_{features}}$) and samples ($\boldsymbol{S_{samples}}$). Then, a tree is generated using $\boldsymbol{S_{samples}}$ with the chosen features $\boldsymbol{S_{features}}$.

During the testing phase of the RF algorithm, the input vector is $[rssi_1, rssi_2, ..., rssi_N]$ which contains the measurements of different APs. Each tree produces an estimated location $\boldsymbol{\hat{y}_i}$ and the output of the RF algorithm is $\boldsymbol{\bar{y}}$ as the average of all estimated locations. In the testing phase, we know the real location where the measurements are collected. Thus, the quality of the estimation by the RF can be analysed. The proposed approach has a significant advantage in that it is computationally efficient that can be used for real-time applications.

Algorithm 1: RF algorithm

- ■ To model the forest (training):
- • **Input:** $([\boldsymbol{R}(1), \boldsymbol{y_1}], ..., [\boldsymbol{R}(T), \boldsymbol{y_T}])$
  foreach *i=1,...,S* **do**
  - -- Select a random subset of features ($\boldsymbol{S_{features}}$) from the input data
  - -- Extract a random subset of the samples ($\boldsymbol{S_{samples}}$)
  - -- Build a tree using data of $\boldsymbol{S_{samples}}$ with the selected features $\boldsymbol{S_{features}}$

  end foreach
- ■ To predict the final location:
- • Input the new vector of measurement $[rssi_1, ..., rssi_N]$
  foreach *i=1,...,S* **do**
  - -- Estimates the location $\boldsymbol{\hat{y}_i}$ with the new input vector on the i-th tree

  end foreach
- • Output the final position $\boldsymbol{\bar{y}} = \frac{1}{S}\sum_{i=1}^{S} \boldsymbol{\hat{y}_i}$

2) Adapting Boosting (Adaboost)

Adaboost leverages the predictions of multiple individual models, known as *Weak Learners* (WLs), to arrive at a final prediction [42]. The WLs are generated through a process called boosting, which involves iteratively training the model on new subsets of the data, with each round emphasizing the data points that were incorrectly classified in the previous iteration. Figure 4 illustrates the method of combining the predictions of all the WLs in the ensemble to make the final prediction. Two Adaboost-based training algorithms are studied in this work: DTA and LTA. In the DTA method, the positions from various WLs associated with a decision rule are averaged in the final prediction [43], while in the LTA method, an interpolation function is developed between the different outputs within a set of decision rules [37], [38].

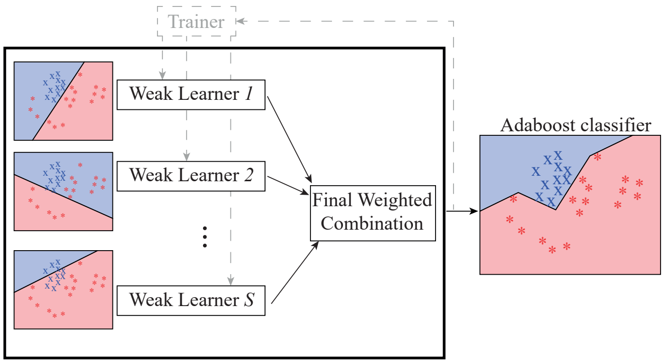

FIGURE 4: Adaboost process

Adaboost is capable of adapting and learning from changes in data over time, making it crucial in dynamic environments where wireless characteristics are prone to variation. Although it achieves high accuracy, especially in LTA, a significant disadvantage of Adaboost is its reliance on extensive computational processing for the final estimation.

The structure and formulation of the Adaboost regressor training, as described in [42], is explained through the pseudocode in Algorithm 2. As in RF algorithm, given T samples and N APs labeled $([\boldsymbol{R}(1), \boldsymbol{y_1}], ..., [\boldsymbol{R}(T), \boldsymbol{y_T}])$ where the input vector is a tuple compound by a RSSI vector formed by $RSSI_n(t)$ from the nth AP and tth sample and the output $\boldsymbol{y_t}$ is the final position of the user in a 2D plane. For the Adaboost, there is a number S that determines the number of WLs (in RF determines the number of trees). On each iteration $i = 1, ..., S$, the regression generates a WL function g_i with an associated weight w_i that adjust the regressor to minimise error. Initially, w_i is set equal to $1/S$. The weighted error e_i defines the error of the regression at the i iteration and sets λ_i. The parameter λ_i defines two characteristics of the regressor. First, λ_i defines the step size of the adapting boosting. Second, λ_i sets the new weight w_{i+1} in the WL. Then, the set of weights w_i are normalized for the next iteration. The final regression model $F(x)$ computes the combination of the weighted WLs that is the weighted average in DTA and the weighted linear regression in LTA.

The estimator uses $F(x)$ for the testing or exploitation phase. In these phases, the input of the regressor is a vector $[rssi_1, rssi_2, ..., rssi_N]$ with the measurements of the APs extracted from the UE. The output of the algorithm is the estimated location $\bar{\boldsymbol{y}}$ of the UE.

Algorithm 2: Adaboost algorithm

- **Input:** $([\boldsymbol{R}(1), \boldsymbol{y_1}], ..., [\boldsymbol{R}(T), \boldsymbol{y_T}])$
- Initialize weights $w_i = \frac{1}{S}$ for every i
- Start with the null classifier $f_0(\vec{x}) = g_0(\vec{x}) = 0$ [**R** (1),

foreach *i=1,...,S* **do**
-- Fit some weak learner g_i
-- Calculate $e_i = \frac{\sum_{j=1}^{S}(e_j * w_j)}{\sum_{j=1}^{S} w_j}$
-- Set $\lambda_i = \frac{1}{2} ln\left(\frac{1-\varepsilon_i}{\varepsilon_i}\right)$
-- Update weights: $w_{i+1} = w_i e^{-\lambda_i y_i g_i}$
-- Normalize w_i to sum to one
-- The new model is $f_i = f_{i-1} + \lambda_i g_i$

end foreach
- Output the final model $\bar{\boldsymbol{y}} = F(x) = \sum_{i=1}^{S} \lambda_i g_i$

III. FUSION OF WI-FI/5G TECHNOLOGIES

As the demand for connectivity increases, the number of radio technologies available at a specific point in space has increased over time. This is especially true for indoors environments, where the demand for broadband is higher. Thus, it is common that technologies such as WiFi and cellular networks are present in most indoor scenarios.

The fusion of 5G and WiFi can also enhance the user experience by providing seamless connectivity [44]. This is particularly important in indoor environments where users frequently move between different rooms and areas, each with varying signal strengths and qualities. With the integration of 5G and WiFi, the system can dynamically switch between the two technologies depending on the location and signal strength, ensuring a consistent and reliable connection.

Moreover, the fusion of these two technologies can also improve network efficiency and reduce costs [45]. With the increasing demand for high-speed connectivity, network operators are under pressure to provide faster and more reliable services. By utilizing both 5G and WiFi technologies, operators can optimize the use of available resources, thereby reducing network congestion and improving overall network performance. This can result in lower costs for both the network operator and the end-user [46].

In terms of localization, 5G and WiFi are two technologies that can be utilized to increase the coverage area, enhance the accuracy of the final location estimate through fusion in trilateration [27], or create denser areas for radio map creation. Furthermore, since both services are managed independently, they can act as backup options for each other in case one fails. Additionally, both technologies can offer unique services, such as wide spectrum service in case of 5G [47] or precise timestamp in trilateration for WiFi [48].

In this work, the fusion of 5G and WiFi, for the different localization algorithms, enables the system to expand the number of APs available for the radio map creation. Having a higher number of APs in the radio map allows the method to compare the context of the UE more thoroughly for the final location estimation. Moreover, a denser radio map reduce the impact of losing a single gNB or APs.

IV. EXPERIMENTAL SETUP

This section presents the configuration for obtaining real 5G data and WiFi from the University of Malaga. The 5G network belongs to the University of Malaga, and contains three indoors base stations which have been configured to reduce the interferences with commercial networks. The base stations are located at two different heights (2.5m and 3.5m) and a map of the scenario is shown in Figure 5. The three WiFi APs are Google WiFi mesh routers placed on shelves at a height of 2 meters. Measurements were taken at *ground truth* points represented by orange dots and green dots. The scenario includes three laboratories and one hall with metallic elements that can cause signal blocking, attenuation, and multipath effects. The 5G gNBs are placed in the ceiling to provide good visibility and transmit at a power of 20 dBm at a frequency of 3774.990 MHz. Measurements were taken systematically over a grid of points marked on the floor as illustrated in Figure 5. Samples were taken 0.8 meters apart to cover the entire accessible area of the scenario.

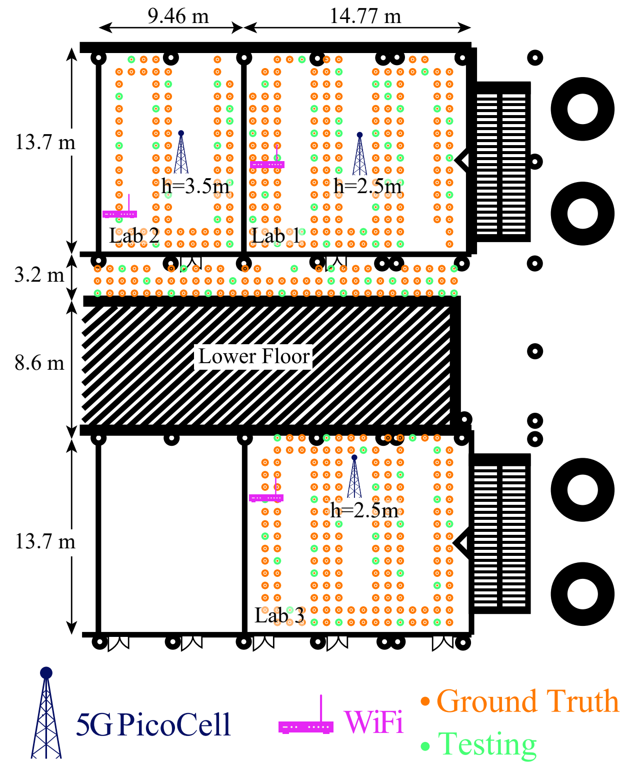

FIGURE 5: Map of the scenario

The location target UE is a Motorola Edge 20 which runs Android 11. An application has been programmed to capture the RSSI of the serving and neighbor cells. The captured data is sent to a server over 5G, where the measurement samples are saved in a MySQL database to be further processed. The programmed application also allows to indicate the ground truth and send it along the taken measurements.

V. RESULTS

In this section, we present the localization results obtained from three different experiments. All experiments used a dataset of over 500 samples. The data was randomly split into a training set and a testing set (represented in Figure 5 as orange and green dots, respectively) with 20% of the measuring points allocated for testing. This process was repeated a thousand times, on each iteration the training and testing points are randomly chosen, using the Monte Carlo method, in which Figure 5 represents one example of this process, to produce accurate statistical results.

A. EVALUATION OF DIFFERENT METHODS

This experiment evaluated the performance of four localization techniques - fingerprinting, DTA, LTA, and RF. The DTA and LTA methods were trained with 50 WLs as suggested in [49], and the number of trees in RF was set at 50 for fair comparison with Adaboost. In this experiment, the performance of the different methods is being evaluated solely using 5G technology. For fingerprinting, the training data was used to construct a radio map and for the rest of the methods, the training data was utilized to construct the trees or the WLs. The testing data was used to measure the precision of the different localization methods, with the results represented by the Cumulative Distribution Function (CDF) of the horizontal error in Figure 6. The 95th percentile (horizontal pink line) has been selected as the basis for location accuracy standard [50].

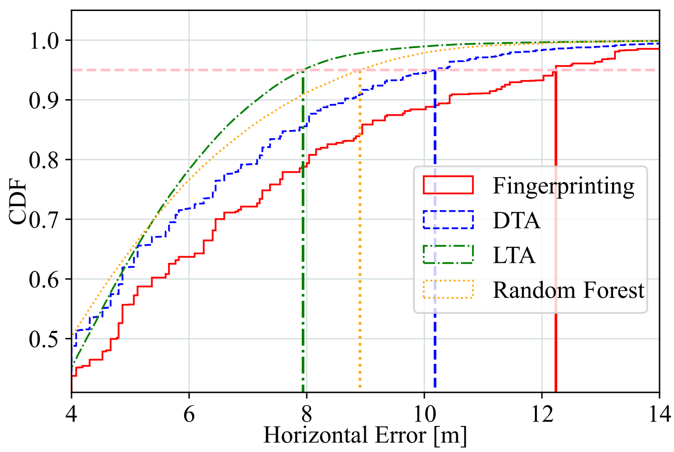

FIGURE 6: Cumulative Distribution Function of the error of different methods with 5G data

Fingerprinting (red) estimates the position of the UE on the radio map by identifying the closest point. The radio map is divided into a lattice, and fingerprinting determines the location of the UE within this lattice. DTA (blue) calculates the average the output of the different WLs. In case of averaging a regular radio map, the final result is always a lattice of the radio map. Notably, all measurements are acquired at the center of these lattices. Thus, both fingerprinting and DTA provide a lattice-based location that is translated into discrete error and a staggered step of the CDF. In contrast, RF (yellow) averages the linear estimation that produces a linear output while LTA (green) generates a more precise estimation by interpolating the different outputs of the WLs. Contrary to fingerprinting and DTA, RF and LTA have a continuous CDF since the final location is estimated across the entire space.

Figure 6 clearly shows that ML methods significantly reduce errors compared to the fingerprinting technique. The accuracy of fingerprinting heavily relies on the radio map as it compares directly with the received signals from the UE. RF and LTA enhances the final location estimation compared to DTA because the final position is derived from a linear function. While LTA provides higher precision in positioning, it is not feasible for real-time applications due to its highly time-consuming nature. RF offers a trade-off between accuracy and computational efficiency, making it suitable for real-time applications.

B. EVALUATION OF FUSING TECHNOLOGIES

In this experiment, the behavior of the different algorithms are evaluated with different cases: with 5G and WiFi in isolation and the fusion of both. The goal was to determine if fusion enhances the precision of the localization system when different technologies appear in fingerprinting and DTR-based methods.

Although 5G promises high-precision positioning through the multi-RTT protocol, to the best of the authors' knowledge, this protocol has not been implemented in any commercial device yet. On the other hand, WiFi has already created the 802.11mc protocol, which offers accurate ranging estimation through the RTT protocol and can achieve meter-level accuracy [9], [48]. This protocol is widely implemented in plenty of smartphones, but only a limited number of APs have adopted it [51]. Until RTT protocol gets integrated into 5G, using ML techniques and fingerprinting along with RSSI measurements can be highly beneficial. Additionally, capturing RSSI measurements does not increment the energy consumption of the terminal or demand special hardware [9].

Figure 7 represent the different cases of fingerprinting, DTA, LTA and RF with only 5G NR (solid line), only WiFi (dashed line) and fusion of 5G and WiFi (dotted line). As it can be observed, fusion improves the performance of the system in all cases. Combining different technologies increases the number of APs in the scenario, which improves the final estimation due to the availability of more information of the environment. So, the more complete radio map, the better localization resolution will be. Among the techniques, fingerprinting yields the greatest improvement as it is the most radio map dependent. Despite of LTA having a slightly better overall performance, RF still provides a high level of accuracy that is comparable to LTA and it allows real-time location-based services.

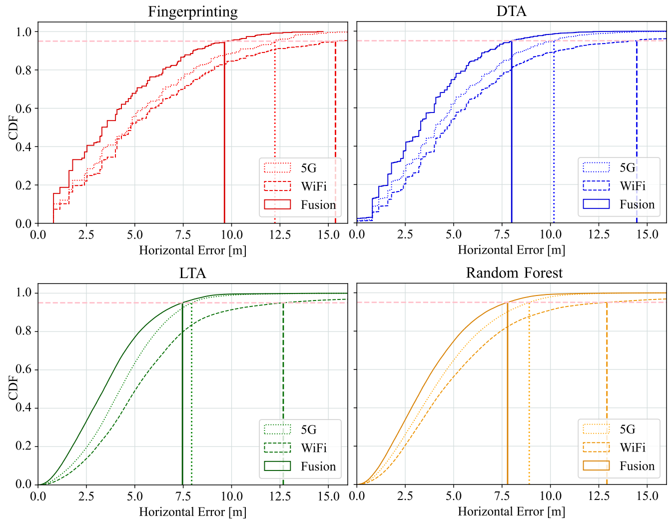

FIGURE 7: Cumulative Distribution Function of the error of 5G, WiFi and fusion for different methods

Table 2 presents the performance of the different algorithms for 5G, WiFi and fusion data, characterized by metrics including the mean (μ), median (Mdn), Root Mean Square Error (RMSE), standard deviation (σ) and the 95% percentile of cumulative density error. All measurements are presented in meters for reference.

C. ROBUSTNESS OF THE METHODS WITH DIFFERENT PERCENTAGE OF MISSING DATA

In this experiment, the robustness of the different methods are evaluated with varying degrees of missing data. In this case, the fusion of 5G and WiFi is used as the input data because it has demonstrated to always improve the performance of the localization results. The goal was to determine the robustness of the techniques by examining how well it performed as the percentage of missing data in the radio map increased. This experiment consists on reducing the number of training points. To do this, the percentage of testing points was kept constant at 20% while the percentage of discarded data varied from 0% to 60% as shown in Figure 8.

The results of the experiment were represented by the CDFs of the horizontal error when different percentages of discarded data (0%, 20%, 40% and 60%) are used to evaluate the performance of the system. As it can be observed

TABLE 2: Performance comparison of different methods with 5G, WiFi and Fusion

	5G					WiFi					Fusion				
	μ	Mdn	RMSE	σ	95%	μ	Mdn	RMSE	σ	95%	μ	Mdn	RMSE	σ	95%
Fingerprinting	5.21	4.77	4.45	3.52	12.23	6.15	4.8	5.56	4.90	15.36	4.06	3.29	3.52	2.88	9.63
DTA	4.6	4.07	7.17	2.97	10.18	5.71	4.66	7.38	4.47	14.46	3.61	3.29	6.90	2.40	8.0
LTA	4.39	4.25	3.45	2.12	7.93	5.77	5.06	4.92	3.87	12.67	3.63	3.40	2.96	2.06	7.46
RF	4.33	3.98	3.69	2.46	8.9	5.42	4.49	4.85	4.95	12.91	3.70	3.36	3.24	2.19	7.78

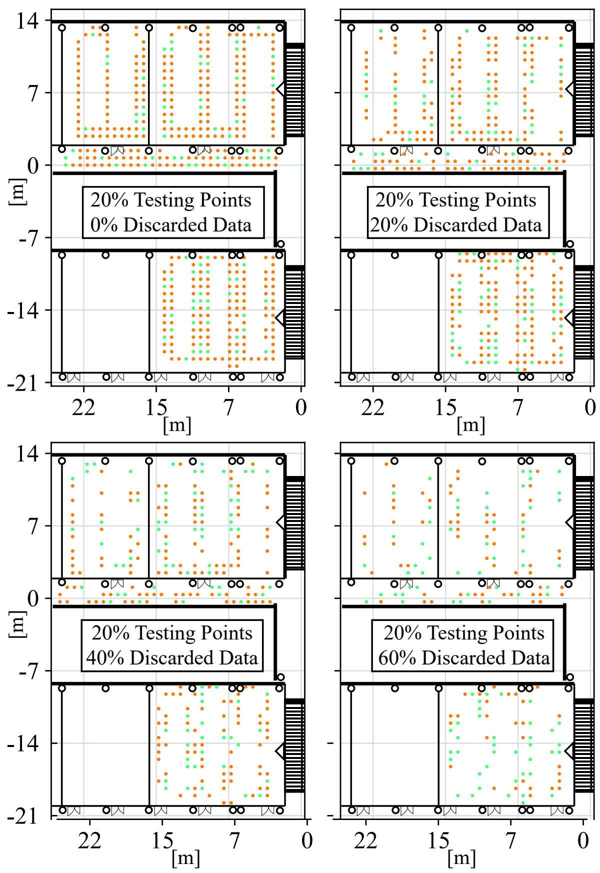

FIGURE 8: Experiments with different percentage of discarded data

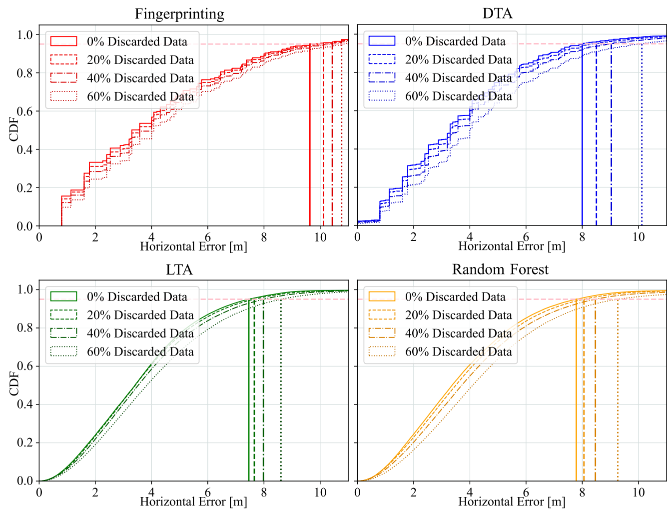

FIGURE 9: Cumulative density distribution of the error of different techniques with different percentage of discarded data

in Figure 9, except of the case of DTA with 60% of discarded data, the rest of the cases of DTR-based algorithms outperform fingerprinting without discarded data in terms of user localization accuracy. Therefore, using DTR-based algorithms, allows to achieve higher levels of accuracy even with maps that contain fewer data points.

Table 3 provides a brief summary of the different methods.

VI. CONCLUSIONS

Indoor positioning has become an increasingly important technology in recent years as it enables a wide range of applications, such as indoor navigation, asset tracking, and location-based services. However, the traditional method of using radio maps for indoor positioning has several significant drawbacks. One of the most significant issues with radio map techniques is the complex training process required. The process of creating a radio map involves collecting and analyzing a large amount of data from a given indoor environment. This data is used to build a map of the radio signal strength for each location in the area. However, this process can be time-consuming and expensive, which limits its applicability in scenarios where a large area must be covered. Moreover, another major issue with radio map techniques is that the fingerprints of the indoor environment can change over time due to changes in the scenario. These changes can affect the accuracy of the radio map, which requires frequent updates to maintain the effectiveness of the technique. This retraining can be very costly, both in terms of time and resources.

In this work, we have performed and compared fingerprinting, DTA, LTA and RF techniques with real 5G and WiFi data. First, DTR-based methods noticeably improves the localization performance compared with the regular fingerprinting. It is remarkable that LTA and RF have performed

TABLE 3: Comparison of different methods

Method	Advantages	Disadvantages
Fingerprinting	Efficient and simple Suitable for real-time applications	It requires frequent updates on the map Not precise
Random Forest	It can handle large amount of data Robust to overfitting and can handle missing data Relatively simple	Does not adapt to changes Significant computational resources for training
DTA	Adapts to changes in the environment Robust to overfitting and can handle missing data	Not as effective as other methods Computationally intensive
LTA	Adapts to changes in the environment High accuracy Reduced frequency of retrainings Allows for larger radio maps	Computationally intensive Not suitable for real-time applications

better than DTA and fingerprinting because the final location based on the interpolation between points.

On the other hand, fusion of technologies have proven to provide better performance of the system. By combining 5G and WiFi, the number of APs in the scenario increases. This implies that during both the training phase and the operational phase, the different localization algorithms are provided with more information about the environment. This, in turn, results in improved final estimation by providing more environmental information. Furthermore, fusion has the potential to enhance connectivity, extend coverage, optimize resources for location-based services and minimize the expenses associated with deployment and infrastructure.

Related to the robustness of the different methods, LTA and RF maintains the error stable even when the percentage of missing data becomes significant, up to 40% of missing data. Its robustness allows to cover larger areas, minimize the need for frequent retraining, or decrease the number of data points required on each map. Depending on the service being offered, DTR-based models, specifically LTA and RF, can be highly valuable tools for indoor positioning. In these experiment, LTA yields better results in both experiments than RF but it is not suitable for real-time applications. Nonetheless, RF provides a balance between accuracy and computational efficiency, making it ideal for real-time services. Although RF cannot adapt to environmental changes, DTA readjusts to them but with decreased localization accuracy. As a result, DTR-based models have imposed its applicability over fingerprinting. However, there is no single method that is universally best for location-based services, as it varies depending on the specific application and scenario.

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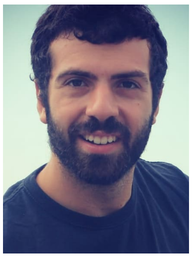

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Victim Detection and Localization in Emergencies

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Abstract: Detecting and locating victims in emergency scenarios comprise one of the most powerful tools to save lives. Fast actions are crucial for victims because time is running against them. Radio devices are currently omnipresent within the physical proximity of most people and allow locating buried victims in catastrophic scenarios. In this work, we present the benefits of using WiFi Fine Time Measurement (FTM), Ultra-Wide Band (UWB), and fusion technologies to locate victims under rubble. Integrating WiFi FTM and UWB in a drone may cover vast areas in a short time. Moreover, the detection capacity of WiFi and UWB for finding individuals is also compared. These findings are then used to propose a method for detecting and locating victims in disaster scenarios.

Keywords: detection; localization; UWB; WiFi FTM; victims

1. Introduction

Disaster management is a topic of the utmost importance in modern society. Naturally, as Information and Communication Technologies (ICTs) progress, novel applications are found for disaster management. These applications are subject to very challenging environments in disasters, where existing infrastructure (such as Base Stations (BS) or Access Points (APs)) is often inaccessible, time is a limited resource, and danger for rescuers and victims is present at all times.

One of the most challenging tasks in a disaster scenario is the detection and localization of victims, especially in disasters that involve being trapped under rubble. Detection and localization comprise the first in a series of steps [1], which also include the assessment of the victim's status, communication, release and, transfer to a safe localization. The localization task is performed traditionally either with direct observation by the first responders (often with prior approximate information on where the victims might be located) [2] or with trained canine units [3].

With the emergence of wireless networks, many new possible applications for disaster management are enabled. Firstly, mobile networks provide an infrastructure-free connectivity from the point of view of the users, making the deployment of connected first responder assistance equipment immediate and simple. Secondly, since connected devices are ubiquitous, the victims are also often within reach of (or very close to) them, increasing the chances of detecting, locating, or communicating with them. To successfully localize victims within a disaster scenario, a gross estimation with a precision below 200 m is required [4]. This requirement is more relaxed than localization for other common location-based services currently under research (such as self-driving vehicles [5] or augmented reality [6], which demand centimeter-level accuracy); however, the context of the devices is much more challenging (e.g., with partially operational infrastructure or under rubble).

In the next few years, most of the smartphones will integrate UWB chipsets [7,8] and/or support the WiFi FTM protocol [9]. Following the trend of the market and knowing the advantages that both technologies bring for indoor positioning, UWB and WiFi FTM are likely to become the de facto positioning technologies for indoors [10–13]. From the

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victims' perspective, the tendency of the integration of UWB and WiFi FTM in the chipsets makes the cost associated with this integration virtually null.

The contributions of this paper are the study of the role of wireless networks, in particular UWB and WiFi FTM, in the detection and localization of victims in disaster scenarios, specifically under rubble, providing an overview of the existing methods, their degree of implementation, and their precision. In addition, in this work, a scheme for opportunistically locating devices using several technologies for application in emergencies and a proof-of-concept using real devices are presented.

The rest of the paper is organized as follows. In Section 2, an overview of the challenges in locating victims in disasters is provided along with a review of existing solutions. Section 3 provides an overview of the different location technologies, explaining their features used in this work. In Section 5, the proposed opportunistic fusion method is described, along with the particularities of using it in emergency scenarios. The proof-of-concept and the scenario are described in Section 6. In Section 7, the results are presented and discussed. Finally, the conclusions are reviewed in Section 9.

2. Challenges of Detection and Localization of Victims under Rubble

Rescuing people in the first 48 h, also known as the golden hours [14], is crucial. After this time period, the chances of survival drop off drastically. Thus, a fast and efficient deployment is essential in these emergency cases. In this section, an overview of the challenges of locating victims and the methods used in the real world is provided.

There are many different kinds of disasters that imply having to find and rescue people in hazardous environments. Some typical examples are earthquakes, mass or individual transportation accidents, terrorist attacks, or extreme weather. When one of these situations occurs, the environment where the victims are located suffers rapid and traumatic changes, such as building collapses, flash floods, or fires. Of course, no two disasters are alike, since the victim's status, the resources available for the first responders, and the dangers for both depend on very scenario-specific factors, sometimes even depending on the personal traits of the involved actors. Consequently, victims may be located in many different places, depending on the type of disaster and the specific factors.

Finding victims in these situations is especially challenging, and while the challenges are very situation-specific, some general situations can be described:

- Victims are in hard-to-reach places, such as under rubble or inside deformed vehicles. This challenge has different degrees of difficulty, depending on how hidden the victim is. For instance, in building collapses, victims that are on the top floors are easier to detect and rescue than those that are on lower floors [15], which are more isolated under a thicker layer of rubble. In traffic accidents, the type of vehicle, passive safety systems, speed, etc., play a central role in the outcome of the rescue mission.
- Victims often cannot collaborate, if they are incapacitated due to wounds or being trapped. In the worst case, the victims may be unconscious, making them harder to find.
- The lack of support infrastructure, such as pavement to ease the evacuation of victims in ambulances, cell towers that allow telecommunications for coordination [16], electricity, etc.
- Time is often limited [14] to find and rescue victims, which may be wounded and need medical attention. As time increases, the physical and psychological pressure on victims may cause permanent damage [17].
- First responders (and victims) are subject to hazards such as falling structures, flammable and/or toxic gas leaks, replications of the disaster, etc. Therefore, there is an even higher need for rescue missions to succeed in the shortest possible time.

Depending on the kind of disaster and the specific context of the victim, they can be classified into two separate groups: surface and underground victims.

Surface victims are those that end up exposed above possible debris. This is common in situations such as floods, terrorist attacks, or earthquakes. Localization needs to be performed in two dimensions and with a relatively low precision, since once the first responders are nearby, they can easily locate and access the victim. Surface victims can be located with relatively simple techniques, such as human visualization or detection with rescue dogs [3]. More recent IT-based solutions have been proposed, such as audio- [14] or image-based [18] based human detection from Unmanned Aerial Vehicles (UAVs). These techniques use the signals from the UAV's sensors and process them in real-time with techniques such as life signs detectors using drones in disaster zones supported by deep learning [19], which, paired with the GNSS location, can help to pinpoint the victims on a map. A detailed description of such a system for flood victims was described in [20]. Another prototype has emerged for surface extraction that places an autonomous wristband on the victims for monitoring their vital signs and easing the rescue [21].

In contrast, underground victims are extremely challenging to find due to visibility and sound being blocked by rubble. In [14], they implemented an audio-processing-based human detector with a UAV even under rubble. The victims needed to be located in three dimensions, in order to better assess their situation, communicate with them, and estimate their chances of survival. Moreover, the precision requirements were higher, since rescuing underground victims often involves complex and risky procedures to liberate them. Finding Individuals for Disaster and Emergency Response (FINDER) uses radar for detecting heartbeats or breathing variations of the victims [22]. However, underground techniques are extremely complex and cover a limited area. To overcome this limitation, the DronAid system proposed in [15] uses Passive Infrared (PIR) sensors mounted on a UAV to scan the rubble, looking for victims trapped near the surface. Table 1 compares the different victim detection and localization systems described above compared with the proposed method. The crucial characteristics that we compared were: the capability of finding individuals under rubble, a fast deployment to find victims, and the precision of the victim's location.

Table 1. Overview of different methods and prototypes for the detection and localization of victims.

	Find Individuals under Rubble	Fast Finding of Individuals	Precision
Visual recognition with rescue dogs [3]	No	Yes	High
Life signs detector using a drone in disaster zones [19]	No	Yes	High
Audio-processing-based human detection in disaster sites with unmanned aerial vehicle [14]	Maybe	No	Low
DRONAID [15]	Yes	Yes	Low
Methods for autonomous wristband placement with a search-and-rescue aerial manipulator [21]	No	No	Precise
FINDER [22]	Yes	No	Precise
Victim localization using Bluetooth Low-Energy sensors [23]	Yes	Yes	Precise only at the surface
Detection and location of victims using WiFi FTM and UWB	**Yes**	**Yes**	**Precise**

3. Overview of Location Technologies

In this section, an overview of precise technologies for positioning, which have been designed for challenging scenarios such as indoors, are described below.

3.1. Cellular-Based Radio

Cellular networks are currently widely used and ubiquitous, making them present in most disaster scenarios [24]. New functionality has been added generation after generation, and currently, the Fifth-Generation (5G) is being deployed around the world. The availability of radio signals, which can be measured and used for ranging, makes them an ideal candidate for detection and localization of personal devices in disaster scenarios. 5G works on the 700 MHz, 3.5 GHz, and millimeter waves of the 26 and 28 GHz bands. Higher frequencies allow high-precision ranging in direct Line of Sight (LoS) with the target, but highly suffer from attenuation, multipath, and reflections in Non-Line of Sight (NLoS). In contrast, lower frequencies are more robust to attenuation, reaching longer distances; however, multipath effects can deteriorate the precision of the ranges. In [25], in order to eliminate the need for clock synchronization, the use of different timing techniques such Round-Trip Time (RTT) was proposed for indoor localization.

5G NR with millimeter waves fulfills the specifications of Release 16 [26], which requires a localization error below $\leq$3 m in the horizontal and vertical planes in indoor deployments and $\leq$10 m in the horizontal plane and $\leq$3 m the vertical plane outdoors [27]. To the best of our knowledge and due to the early-stage deployment of 5G millimeter wave technology, there are no experiments with real data that measure the real accuracy of the system, despite the existing terminals that work with mmWave [28]. However, in [29], a study based on simulations concluded that the final accuracy fulfilled the requirements. Hence, in case the 5G network cannot provide coverage where the LTE network can, UEs may benefit from LTE as a backup for other location technologies [13,30]. End-users may benefit from cellular localization in cases where no high-precision technologies are present. Older cellular generations, such as 4G, usually provide a lower precision compared to 5G. For instance, LTE utilizes the Received Signal Strength Indicator (RSSI) for ranging. RSSI highly suffers from multipath and fading, which lead to high variations and an increase in the ranging error.

3.2. Ultra-Wide Band

UWB stands out as one of the most-promising technologies for indoor localization [31]. It is becoming a de facto standard for indoor localization, with a growing adoption in the market [7]. UWB technology utilizes very short pulses (in the order of nanoseconds), which are translated into a wide bandwidth. This enables high data transmission rates and high-precision ranging with good obstacle penetration capabilities [32] and robustness against multipath effects in NLOS conditions [33], making UWB outstanding at detection and positioning in emergency scenarios. Thus, UWB has been previously indicated as a possible human detection technology in complex environments [34] or as an impulse radar [35].

3.3. WiFi

WiFi is another ubiquitous wireless technology (although mainly in indoor scenarios and with small deployments) used for communications. It is made up of different versions of the IEEE802.11 protocol family, which are supported by a very wide base of consumer devices for communications. Two different approaches of WiFi are widely implemented for location services.

3.3.1. WiFi Fingerprinting-Based Localization

This is one of the most commonly used technologies and algorithms used for indoor localization [36] due to the ubiquity of WiFi networks and its low cost. Fingerprinting consists of two phases: offline training phase and online operating phase. During the offline phase, a radio map divides the scenario into a lattice, and the RSSI of the visible routers at each point of the lattice is stored. In the online phase, the system estimates the UE position, comparing the RSSI information to the most similar entry of the radio map. However, this technique cannot be used in emergency cases due to the changes in the environment, making ranging–location systems crucial for locating victims. The main issue of all fingerprinting techniques in emergency scenarios is the fact that one cannot create a radio map in the offline phase. When the catastrophe comes, such as an earthquake or flooding, the scenario completely changes, and the radio map becomes useless for localization service.

3.3.2. WiFi Fine Time Measurement

More recently, the IEEE 802.11mc variant added a new Fine Time Measurement (FTM) functionality. FTM includes timestamped packets and calculates distances to the User Equipment (UE) accurately with the Round-Trip Time (RTT) protocol [12]. This may be very useful for emergency cases because the number of smartphones that include support for this protocol is increasing [9]. The distance calculation to every router that supports the FTM and RTT protocol is computed in the UE for privacy preservation, even if the UE is not connected to the router.

3.4. Bluetooth Low-Energy

Bluetooth Low-Energy (BLE) is also another omnipresent wireless technology used in Personal Area Networks (PANs) for data transmission. Several studies have researched within the scope of detecting, localizing, and tracking people in indoor scenarios [37–39]. Most of these studies work in indoor spaces, applying methods such mapping and fingerprinting, which require previous knowledge of the terrain. In this work, we assumed a potential collapse of the infrastructure due to flooding or an earthquake, which makes fingerprinting techniques unfeasible for localizing victims, due to the outdated maps collected prior to the collapse.

4. Victim Detection

Immediately after a catastrophe, a key aspect is to detect and account for the victims trapped under the rubble, after which localization can be performed to further concentrate the efforts of the first responders. Several techniques have been proposed for this task:

- Visual recognition with rescue dogs: the traditional task of finding victim is usually performed either by direct observation or with the help of trained rescue dogs [3].
- Human body image detection: when the victims are incapacitated, image recognition may help to find individuals that are on the surface [19,21].
- Audio-processing-based human detection: when victims are trapped under rubble and there is no visual or imaging recognition, drones may integrate microphones to detect any distress calls and notify the rescue services [14].
- Vital signs detection: Passive Infrared (PIR) sensor for detecting victims that are buried close to the surface [15]. PIR reacts only to certain energy sources such as human body heat. Low-power microwave radar signals can be used to detect the heartbeat and breathing of underground victims. The limitation of such devices is the short coverage of some meters [22].
- Localization using radio signals coming from devices that victims carry (e.g., smartphones) or wear (e.g., smartwatches): this paper relies on this method for detecting and then locating the victims [23].

5. Victim Detection and Localization Method

Drones or Unmanned Aerial Vehicles (UAVs) will play a key role in the detection and localization of victims in emergency scenarios. Several research works have used drones for finding individuals under rubble with camera recognition [15,19,21]. Drones can also act as mobile Access Points (APs), which provide network connectivity both to the first responders and to the victims, who can potentially use the drones to transmit their information. User devices that integrate WiFi interfaces periodically send a control frame to have the nearby wireless access points' information [40]. For this work, we exploited this scanning procedure from the user side to detect different devices in the area and listed by their MAC address. Once the victim is detected, more drones will approach the victim's location by looking at the RSSI values. When a sufficient number of drones is in the vicinity of the victim's location, the localization will be determined by using trilateration. Basic trilateration obtains the position of the target in 2D based on the intersection of the distances from at least three reference points; for 3D, at least four reference points will be needed. In this case, the ranging information must be obtained by timing measurements, which may enhance the accuracy of the victim's position compared with the RSSI ranging performance. Figure 1 illustrates drones scanning the surface looking for victims under rubble (in red). Once a victim is detected (in yellow), the drone notifies a central coordination system, and the rest of the air fleet approaches the site to serve as additional reference points and to complement the partially damaged infrastructure. When the victim is located (in green), the system knows approximately the position of the victim and the emergency response will start.

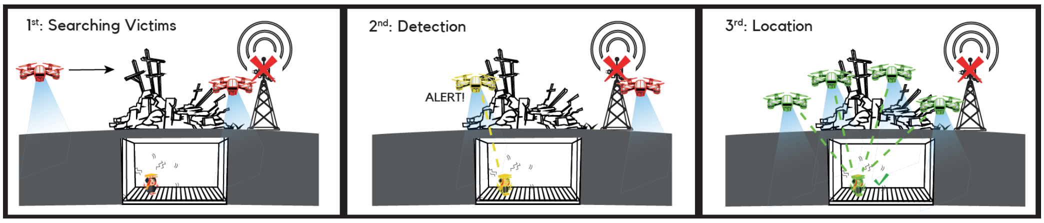

Figure 1. Illustration of the method.

To know the victim's position, it is necessary to have the information of, at least, four reference points. The higher the number of drones providing location information, the more accurate the victim's localization can be. Thus, fusing different technologies can help fulfil or increment the number of visible reference points to augment the accuracy. In [13], opportunistic fusion was proposed using several different technologies for ranging, specifically UWB, WiFi, and LTE. Opportunistic fusion takes advantage of the fact that, in most locations, several different radio technologies are visible and that modern mobile devices support these technologies. Instead of using the reference points and ranges obtained from a single technology (e.g., UWB), opportunistic fusion uses whichever reference points are visible to the device.

The major challenge for this system (and, in general, for localization with mobile devices in a catastrophe) is to collect the measurements of victims under rubble with missing elements in the network. In this paper, opportunistic fusion is proposed for taking advantage of whichever infrastructure is undamaged in a catastrophe (such as cellular network base stations or WiFi routers), complemented with portable reference points (such as drone-mounted WiFi access points with FTM capability or mobile UWB access points), to detect, estimate the distance to, and triangulate the approximate position of the victims. Opportunistic fusion greatly enhances the chances that the victim is within the range of four reference points and, therefore, can be located.

One of the main requirements of this system is to have access either to the UE measurements of the reference points or to the uplink measurements of the network. Either way, the inclusion of additional functionality tailored to accurate localization in the mobile network standards would greatly benefit the implementation of a system such as the one described in this paper. There is, in fact, a protocol that allows the UEs to report localization to the mobile network (from which the proposed system could extract that information) called NRPPa [26]. Currently, this precise localization is obtained with GNSS receivers in the UEs and is reported through NRPPa as estimated coordinates. To fuse different ranges and different reference points, including temporary ones, the following messages should be included [30] as an extension to NRPPa:

- Reference point identifier;
- Reference point location;
- Technology type;
- Timestamp;
- Round-trip time.

6. Materials and Methods

Locating victims under rubble is a very challenging task, so even a gross estimation of where they may be is of great value to first responders. While radio-based methods for detection and localization may be of help, rubble is a very harsh environment for radio propagation. Therefore, there is a need to better understand propagation in this kind of environment. In this section, we insert a smartphone into a pile of rubble over 50 cm thick in all directions to simulate a buried victim. We deployed UWB, WiFi, FTM, and LTE to estimate the location of the UE and obtain accurate horizontal and 3D information.

Rubble was made of several metallic objects such as computers, chairs, desks, and bricks, as shown in Figure 2, in order to emulate a disaster scenario in which the victim has been caught under rubble. The UE used for the experiments was a Google Pixel 3, which supports WiFi FTM. For UWB, we attached a DWM1001 device from Qorvo to the UE using a Bluetooth serial port. The UE was equipped with an Android application that estimates the distances to all the reference points of any technology (UWB, WiFi FTM, and LTE) that are within coverage and sends the estimated ranges to a server, where the localization is computed solving the trilateration problem.

We expected the radio signals to be severely affected by attenuation and multipath, causing estimation errors in the ranges and, therefore, errors in the localization. We found that, for the purposes of better understanding the performance of WiFi and UWB under rubble, this emulated scenario could provide enough realism, as it could be used to assess the accuracy.

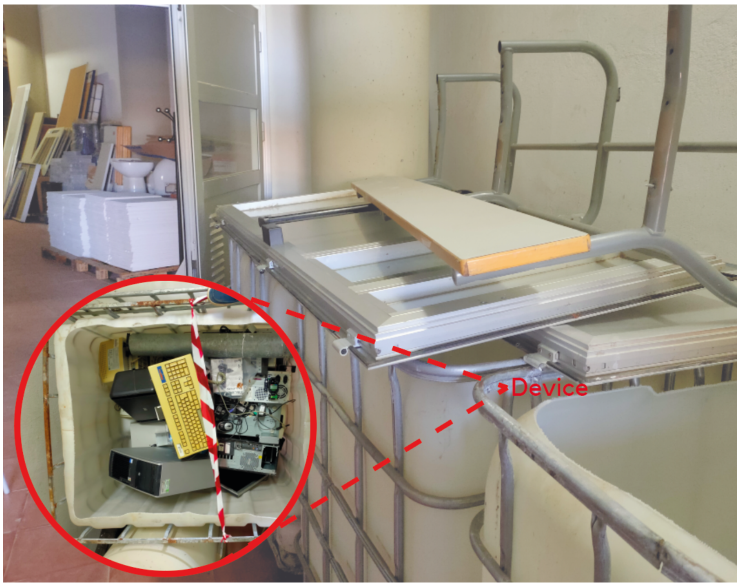

Figure 2. Image of the scenario.

Figure 3 represents the map of the scenario where the UWB (green) and WiFi APs (orange) are placed and the distance to the device under rubble is given. The distance from the UWB (UWB1, UWB2, UWB3, and UWB4) and the WiFi (WiFi1, WiFi2, WiFi3) reference points is indicated next to the dashed line. To clarify the schema, vertical and horizontal views are provided for a better comprehension of the scenario.

The UWB reference points were also DWM 1001 devices, programmed as anchors, and the WiFi FTM was the Google WiFi routers. UWB and WiFi reference points were placed at 2.17, 2.43, 5.93, and 9.27 m away from the victim's device, configured with their default parameters [41], and their heights were 1.16, 0.39, 0.86, and 0.45 m, respectively. The DWM1001's power transmission is −14.3 dBm, and UWB anchors were centered in the 6 GHz frequency band [41].

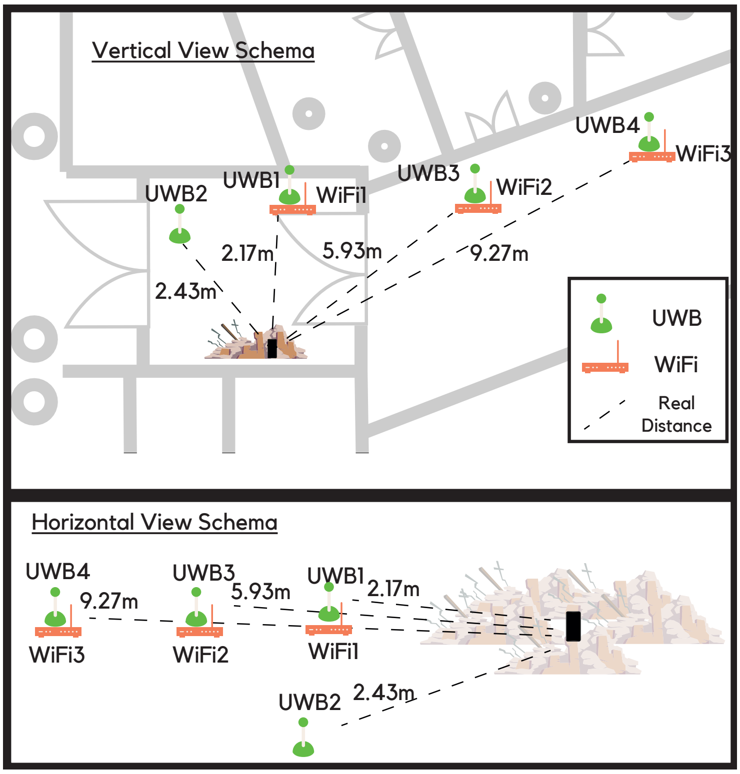

Figure 3. Schema of the position of the UWB and WiFi devices.

WiFi FTM also works on the RTT protocol; hence, its ranging accuracy is also precise. Moreover, the implantation of the WiFi FTM chipset is widely implemented [9]. WiFi FTM APs are part of Google routers' family [42]. WiFi APs were placed next to the UWBs with the same distance and heights from the victim's device. WiFi FTM is centered in the 2.4 GHz band as the typically WiFi frequency and transmits with a power of 28.17 dBm [42].

The LTE network consisted of up to 12 femtocells (of which, 4 were visible to the UE) operated by the research team and located at different floors above the scenario, at 5, 9, and 15 m, and they were configured with a transmission power of −6.8 dBm and downlink and uplink frequencies of 2630 MHz and 2510 MHz, respectively.

The WiFi FTM and UWB ranges were obtained with the RTT protocol, which estimates the distances according the to propagation time. The measured distances were sent to a Flask server, which was run on a laptop with Windows 10 for processing. Measurements were captured during 5 min with a sampling rate of 1 s. With this distribution, the penetration capacity and the ranging-error of UWB and WiFi FTM are calculated.

7. Results

In this section, the results of the measurement campaign are presented. We compared the results obtained from the device under rubble with the ones with the device outside of the pile of rubble.

7.1. Performance of Different Technologies under Rubble

UWB and WiFi FTM are outstanding precise technologies for challenging scenarios such as indoors. Nevertheless, once the device is buried under rubble, the performance of the ranging estimation is degraded by severe multipath and attenuation. Figure 4 shows the ranging estimation error of the UWB anchors (UWB1, UWB2, UWB3, and UWB4) and WiFi FTM (WiFi1, WiFi2, WiFi3) in both cases: under rubble (blue) and outside of the rubble (red). The 80th percentile of error in both technologies increased considerably around 1 m. An important observation was that, during the whole measurement campaign under rubble, no packet was captured by the smartphone from a UWB reference point further than 9 m (as a consequence, UWB4 was left out of the measurements in Figure 4), in contrast with WiFi, which could capture the data without any problems.

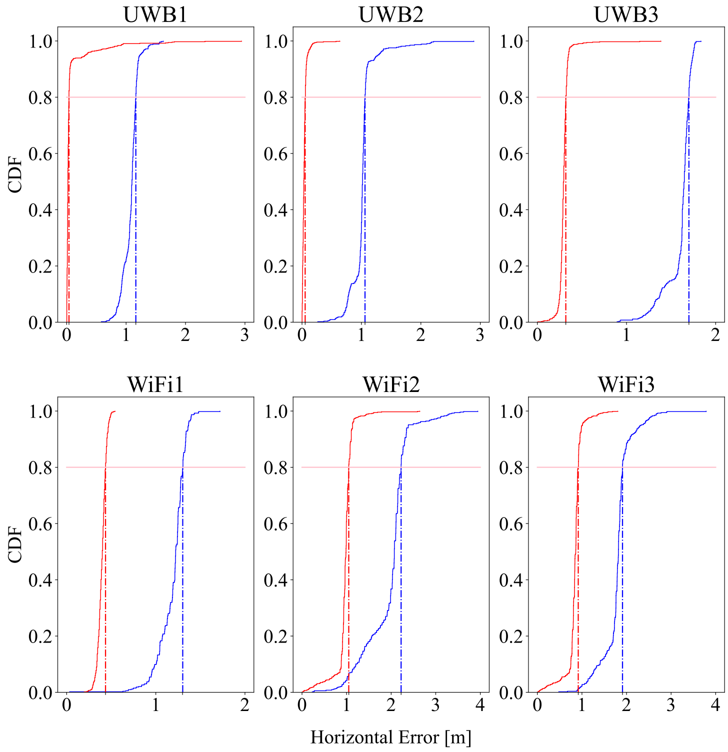

Figure 4. Ranging error of all the reference points with the UE under rubble (blue) and outside the rubble (red).

7.2. Localization Degradation under Rubble

Figure 5 represents the Cumulative Distribution Function (CDF) of the localization error of the victim using the ranges analyzed in Section 7. The positioning error of the measurements under rubble (green dashed line) were compared with those of indoor localization (black line) [13] with the fusion of UWB and WiFi in both. As expected, it can be observed that the positioning accuracy worsened with the obstacles. The pink line represents the 80th percentile, and the error for this point was augmented by 14 m when the victim was under rubble.

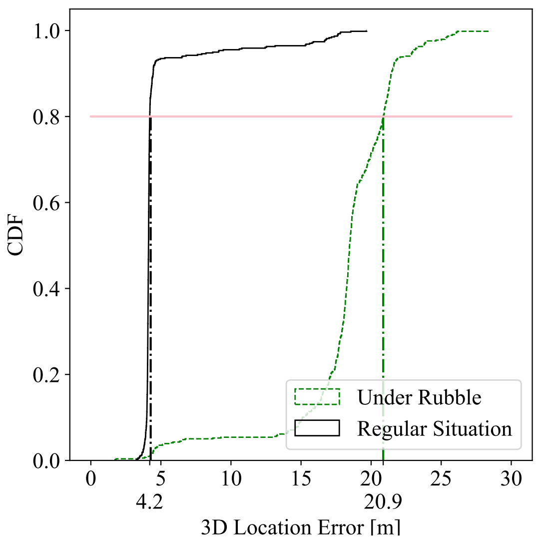

Figure 5. Localization performance under rubble (green) and outside of rubble (black).

8. Discussion

In this section, the results are examined and debated, showing the advantages of using multi-technology fusion for detecting and locating victims when a disaster occurs. While LTE and 5G NR may offer a very gross approximation of the localization, they have serious disadvantages: in a disaster, the fixed infrastructure may be partially or totally damaged; they offer a much lower precision when using RSSI measurements. In this work, the scenario emulated a realistic building collapse to compare the performance of UWB and WiFi in this kind of scenario. We found that WiFi performed better in detection and localization than UWB. However, the use of both technologies is still useful for locating victims. A combination of these high-precision ranging technologies helps to augment the number of ranges, which helps to deal with the interruptions of communication with UWB due to WiFi being stronger. Once the victim is detected, a fleet of drones can approach the place where the victim is located with meter-level precision.

In this work, we showed how the accuracy decreases when a disaster occurs and the victim is found under rubble, as shown in Figure 5. However, we demonstrated feasible drones that can easily integrate the small chipsets. From the victim's point of view, the latest smartphone trends show that the UWB [7,8] and WiFi [9] chipsets are integrated in several smartphones, and the tendency is to increase this number. Thus, the cost associated with this integration is virtually null.

9. Conclusions

People usually typically have a smartphone on them, and in the case of a disaster, such as an earthquake, these devices could be very helpful for finding individuals. Drones are terrain independent and can easily approach a victim's location. The integration of WiFi FTM and UWB with the drones could be crucial for first responder activities to detect victims under rubble. Despite the fact that WiFi presented better results with regard to the accuracy, coverage, and penetration capabilities, as shown in Figure 4, it is worth implementing both UWB and WiFi technologies to improve the inputs to the localization algorithm. Future lines of work are to implement more radio technologies such as BLE or cellular 4/5G due to their multiple advantages: to augment the coverage and probability of detecting and localizing victims, to have higher accuracy in the localization process, and to implement a new protocol that is more stable and faster between the first responder services and the drones. In addition, in the scope of this work, another future goal is to reproduce the experiment in a realistic emergency scenario in a bigger deployment with more realistic damaged infrastructure and the participation of first responders, such as in training installations. Moreover, a study of the integration of a real prototype within the rescue protocols of the first responders may be carried out.

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Exploring Indoor Localization for Smart Education

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***Abstract*—This comprehensive study delves into the realm of indoor positioning technologies within the domain of Smart Education (SE). Focusing on typical techniques and technologies in educational settings, the research emphasizes the importance and potential services of localization in SE. Moreover, this work explores the feasibility and limitations of these technologies, providing a detailed account of their role in educational settings. The paper also contains in an innovative Proof of Concept (PoC), demonstrating an automatic attendance control (AAC) system that integrates 5G and WiFi technologies. This PoC effectively showcases the possibilities and effectiveness of location-based services in educational surroundings even with a limited budget, setting the stage for optimizing teaching time, enhancing the quality of education.**

***Index Terms*—Smart Education, localization, 5G, WiFi FTM, fusion, ML, Random Forest**

I. Introduction

In the last years, the impact of precise location services is growing in society with the advancements in technology, leading to the use of location-based services such as autonomous robots, e-Health or context-aware applications to provide personalized services [1]. By providing more accurate and reliable location information, these services can help improve safety, efficiency, and overall effectiveness in a wide range of industries and applications. Location-based services have also had a transformative impact on Smart Education (SE) [2], where they can be used to improve the overall efficiency and effectiveness by providing real-time information about the location of resources [3], such as classrooms and labs, and the location of students or teachers.

Students are now more connected and engaged when carrying out their academic activities with digital devices. Given the increasing inclination of students to work digitally, the educational infrastructure must satisfy this digital offer towards better future generations. SE consists on the use of the technology to optimize the whole educational system for a personalized teaching and learning process for each student [4, 5]. This includes the use of advanced algorithms, data analytics, and Artificial Intelligence (AI) to create flexible and interactive learning environments that can adapt to the unique needs, preferences, and abilities of each learner [6]. SE utilizes a diverse range of digital tools and platforms, including mobile devices, learning management systems, educational apps, and Virtual Reality (VR) technologies, to develop captivating learning environments [7].

In the context of SE, the need for accurate location estimation is crucial for personalized services. The most common approach for precise localization is the use of Global Navigation Satellite System (GNSS), which provides high accuracy in outdoor scenarios. However, GNSS is not available indoors, where many applications for this field are being developed, due to signal blocking or signal reflections. To overcome this limitation, various technologies and techniques such as 5G and WiFi are being used to provide accurate and precise location information indoors and in built-up areas [8]. Additionally, some applications require the network to estimate the location of end-users in order to save energy and reduce computational complexity [9]. Network-based location is a better solution for these functions, as it allows the network to estimate the location of terminals based on data collected in the network infrastructure without requiring cooperation from the terminals.

This paper provides an overview of the role of localization within the services existing in an SE vertical scenario while also offering insights into potential forthcoming services in the upcoming years. In addition, this work contributes to the development of an Automatic Attendance Control (AAC) system that is carried out as a Proof of Concept (PoC) to demonstrate a location-based service within a resource-constrained SE.

The rest of the paper is organized as follows. Section II provides a comprehensive analysis of various use cases for location-based services in SE. It delves into the requirements and challenges of localization associated with these services.In Section III, various localization techniques commonly applied in the educational settings are explored. Section IV delves into localization technologies that are in the context of SE. In Section V, privacy concerns of localization within an educational context are explained. Section VI explains the PoC, highlighting its objective of AAC through Machine Learning (ML) and detailing the methodology as well as employed classification and regression models. Additionally, the experimental setup and the results are presented and discussed. Finally, the conclusions are carefully reviewed in Section VII. Figure 1 presents the structure of the paper. The acronyms in this paper are listed in the Table I.

II. Localization Services in Smart Education

Education is one of the key pillars of modern society. As human knowledge advances, the topics that are taught become

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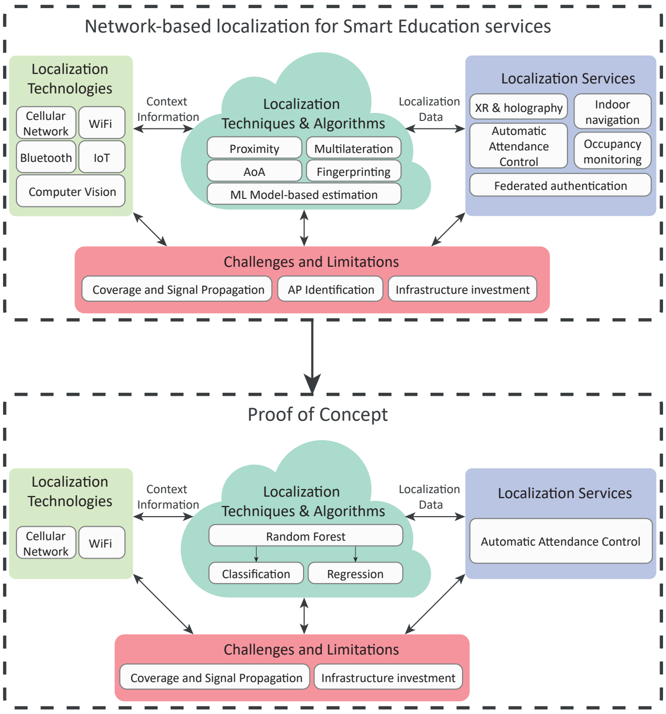

Fig. 1: Structure of the paper

TABLE I: Overview of acronyms

Acronym	Definition
AoA	Angle of Arrival
AP	Access Point
ANN	Approximate Nearest Neighbors
AI	Artificial Intelligence
AR	Augmented Reality
BLE	Bluetooth Low Energy
CSI	Channel State Information
CDF	Cumulative Density Function
DFL	Device-Free Localization
EU	European Union
FR	Frequency Range
GDPR	General Data Protection Regulation
GNSS	Global Navigation Satellite System
gNB	gNodeB
IMU	Inertial Measurement Unit
IoT	Internet of Things
LOS	Line-of-Sight
LS	Least Squares
MIMO	Multiple Input Multiple Output
ML	Machine Learning
MR	Mixed Reality
NB	Narrow Band
NRPPa	New Radio Positioning Protocol A
PAN	Personal Area Network
PIR	Passive Infra-Red
PoC	Proof of Concept
pRRH	pico-Remote Radio Heads
RF	Random Forest
RSSI	Received Signal Strength Indicator
RTT	Round Trip Time
SE	Smart Education
SSID	Service Set Identifier
ToF	Time of Flight
UWB	Ultra Wide Band
UE	User Equipment
VR	Virtual Reality
XR	eXtended Reality
3GPP	3rd Generation Partnership Project

more and more complex and profound, and the teaching methods must evolve and adapt to new layers of complexity [4, 10]. For this reason, education is a very dynamic market, that adopts not only new teaching methods, but also new technologies. Localization, in particular, introduces a diverse range of services aimed at actively involving and inspiring students. In this section, an overview of different localization-based applications in SE are presented.

A. *XR and holography*

eXtended Reality (XR) is a comprehensive term encompassing a range of immersive technologies that merge both digital and physical worlds. It includes VR, Augmented Reality (AR) and Mixed Reality (MR), enabling users to simultaneously immerse themselves in and interact with virtual and real environments [11]. On the other hand, holography refers to the technique of encoding a light field as an interference pattern of phase and amplitude variations. When appropriately illuminated, a hologram diffracts incident light, creating a faithful replica of the initial light field, resulting into a realistic representation of the recorded 3D objects [12]. Both technologies enable an immersive experience that transcends the boundaries of conventional media, offering unique opportunities for diverse applications in fields such as entertainment, education, healthcare, and engineering.

Within the realm of SE, the utilization of techniques like gamification, which involves converting educational concepts into game-like formats and leveraging the brain's dopamine response to improve the learning experience, presents an opportunity to captivate students more effectively and to foster student engagement [13, 14]. Such gamification strategies heavily rely on advanced technologies such as XR or holography [15], which impose substantial demands on processing power and communication capabilities, while also emphasizing the need for physical portability and non-intrusiveness.

By incorporating gesture recognition [16] and location [5], interaction with AR/VR objects can be facilitated, thereby simplifying the complexity and cost of the end devices [17]. Furthermore, location serves as a crucial factor in the traffic generated by SE applications, enabling efficient network management [18]. XR requires a latency below 50 ms [19] and achieves a localization accuracy of 0.1 meters [20]. On the other hand, holography can experience a latency as high as 100 ms [21, 22] while localization accuracy must be below the centimeter-level [21]. When students are situated within a classroom, broadband traffic becomes concentrated in a hotspot. This traffic is similar among students but varies slightly based on their precise location, such as different viewing angles of the same XR object. Hence, if the location is known, the usage of edge resources can be optimized [22].

In the next decade, XR and holography could also be used to create virtual classrooms, where students can attend classes remotely and interact with teachers and classmates in real-time. This could open up new possibilities for education, such as providing access to education to remote and underserved communities [23].

B. Indoor navigation

Indoor navigation is a technology that can be used to provide positioning, guidance and wayfinding for people within a building or campus [24]. To provide a reliable and seamless indoor navigation service, localization accuracy must be enhanced to the level of meter-level in horizontal plane [25] and floor-level in height [26]. This level of precision is necessary to ensure that users can confidently navigate within indoor spaces, avoiding obstacles and reaching their intended destinations accurately. However, by leveraging a combination of position and inertial sensors, including Inertial Measurement Unit (IMU), it becomes possible to achieve a comprehensive and accurate navigation experience even when the localization precision is diminished [27].

Different technologies have claimed to provide precise localization down to some meter-level or lower. For instance, Ultra Wide Band (UWB) technology achieves centimeter-level accuracy with time-based estimations [28] meanwhile WiFi 802.11mc obtains an accuracy of 1-2 meters with the same protocol [29]. 5G claims to provide <3 meters for 80% of the cases, encompassing both horizontal and vertical planes [30] with the aim of indoor navigation. Bluetooth Low Energy (BLE) fulfills the requirements of precision for indoor navigation when mapping the whole scenario in a previous step for fingerprinting [31]. However, fingerprinting is not practical for precise navigation around a whole campus due to the cost of deployment [32]. While 5G or WiFi Access Points (APs) would provide services, mainly internet access, as well as localization features, a BLE-based deployment would not offer additional functionalities except for localization. Furthermore, for indoor navigation systems to be truly effective, a real-time location service is required. Users require instant updates and guidance to make informed decisions while traversing indoor environments. Therefore, the system should operate with a maximum latency of 1 s [33], minimizing any perceptible delays for a fluent navigation response [25].

Indoor navigation can be used to improve the overall efficiency and experience of SE by reducing congestion and making it easier for people to find their way to the desired classroom or laboratory [24]. Moreover, it can set up virtual boundaries, a feature called geo-fencing that triggers an action when a device or a person enters or exits that boundary [34]. Geo-fencing is a powerful tool that is often used in security systems to restrict access to certain areas and ensure that only authorized personnel are present in sensitive areas.

Indoor navigation is also used in emergency situations such as fires, earthquakes, or other disasters where time is crucial, and having a reliable indoor navigation system can be critical to save lives. It can also be integrated with other emergency systems, such as fire alarms, smoke detectors, and emergency lighting, to provide a comprehensive solution for emergency preparedness [35]. In the event of an emergency, the system would automatically trigger an alert, providing immediate guidance to individuals in the affected area making it easier for people to quickly and safely evacuate the building while avoiding certain spaces [36].

C. Occupancy monitoring

Occupancy monitoring is an important issue in SE, as overcrowding can lead to safety concerns, reduced comfort and productivity, and increased wear and tear on facilities [37, 38]. It allows administrators to track the occupancy of different areas in real-time and enforce safe capacity limits. In addition, real-time occupancy monitoring can provide valuable insights into how different areas of the campus are being used, allowing administrators to optimize the use of resources and energy efficiency by combining with different actuators such as lighting or air conditioners, e.g. identifying areas of low occupancy and adjusting the lighting and temperature accordingly.

To accomplish this task, Device-Free Localization (DFL) is a technology that can be used to track the presence and movement of people in a given environment without the need for them to carry any device. There are two types of DFL: based on images and signal propagation.

Camera or vision-based systems combined with ML algorithms provide a centimeter-level accuracy [39]; however, partial occlusion results in coverage blind spots and privacy concerns make this method unfeasible for urban areas [40]. Alternatively, DFL systems based on signal propagation typically rely on WiFi, Zigbee and UWB technologies [40]. When utilizing Channel State Information (CSI), DFL systems capture the multipath propagation during the wireless transmission offering a nonintrusive approach with high sensitivity to channel variations [41]. These inherent characteristics make CSI-based DFL systems within an horizontal error of few meters [42]. Moreover, DFL systems offer a latency below 1 s [40]. DFL can also be based on the Received Signal Strength Indicator (RSSI) between a transmitter and a receiver with LoS [43]. Given that the human body consists of approximately 70% water, it absorbs radio signals, leading to shadowing effects [44]. This process primarily focuses on human movement and tracking [45, 46]. Signal propagation-based DFL systems can be categorized as either model-based [47] or fingerprint-based methods [48].

There are several less effective technologies for nonintrusive DFL, including air-pressure sensing and ultrasound signal reflections [49], Passive Infra-Red (PIR) which detects thermal energy radiation from the human body [50], and CO2 concentration measurement in buildings [51].

D. Automatic Attendance Control

Early attempts at attendance control was a labor-intensive and time-consuming process, and the accuracy and reliability of the attendance data could vary depending on the expertise of the educators. Attendance control is critical for learning, ensuring that students are participating in classes and receiving the education they need to succeed [52].

Over time, advancements in technology have made localization in education more efficient and effective. Up to date, the use of AI and ML has allowed institutions to automatically translate the geo-location of a teacher to attendance control of its workplace when they are in the nearby of the institution [53]. Thus, the rise of SE have evolved to encompass the need for accurate localization data to track students' attendance during lectures [54].

There are different solutions to control the attendance of the students. Camera-based systems identifies with high probability the face of the student to track their attendance [55]. However, this type of system carries significant privacy concerns with additional issue of the subjects often being underage [56]. Barcode or QR scan [57] or RFID identification systems [58] solves these privacy concerns. In barcode or QR systems, students must log in through the institute portal by an application to ensure their attendance by face id [59] or biometrics [60]. RFID identification systems check the attendance based on an NFC system that detects the students at the beginning of the class. QR scanning systems are more time efficient because it makes all students to ensure their attendances in a time interval. Nevertheless, this process halts the lecture for a brief duration.

Automatic attendance control eliminates these processes on the user's side to reduce the time consumed in this process to zero. Moreover, it aids educators in identifying and addressing any issues or challenges that students may be facing, such as absenteeism or lack of engagement. Additionally, attendance data can be used to evaluate the effectiveness of educational programs and make improvements where needed. In short, attendance control is an essential aspect of ensuring that students are receiving a high-quality education.

In [61], an automatic attendance control system based on localization is developed based on BLE. This system matches the localization of the students during the lecture with the attendance control. During this process, neither students nor teacher intervene during the process of attendance control. For this process, time is not critical, so even a latency of up to a few seconds is valid [62]. The location process is done with Approximate Nearest Neighbors (ANN), which is an ML model, that estimates the position of the user by a previous modelling of the scenario. Radio technologies that are usually present in SE scenarios, such as 5G, WiFi or BLE, can also be leveraged for this use. By using the RSSI information, the system can automatically detect the presence of a student in a classroom within a localization accuracy of 2-5 meters [63, 64].

Table II shows an overview of the different use cases with their minimum location accuracy and latency required for the 80% of the cases for 5G commercial use cases [30] and a brief description of their use in SE.

III. Localization Techniques

Depending on the nature of the data information, e.g. signal power, distance or angle to the AP, different approaches are commonly utilized to locate users, including location by proximity, ranging-based methods, Angle of Arrival (AoA), fingerprinting and model-based localization.

Location by proximity is the simplest method for determining the User Equipment's (UE) location, assuming it to be the same as the AP location. This method is employed when high accuracy is not a strict demand [65].

Ranging-based techniques, such as multilateration, involve computing distances to APs using metrics such as RSSI or Time of Flight (ToF) [8]. These methods achieve a high accuracy if the ranges are precise. The final location estimation is determined by the intersection of spheres (or circles in 2D). Nevertheless, range estimations are prone to result into non-convergence of the circles or hyperbolas used in the trilateration process. To mitigate this uncertainty, techniques such as Least Squares (LS) are applied [66].

AoA measures the angle at which the signal arrives at the UE from the AP. This approach is employed in Multiple Input Multiple Output (MIMO) systems because of their ability to utilize beamforming techniques [67]. Indoor environments present challenges for both range-based models and AoA due to signal blocking and reflections [68].

In cases where received power remains relatively constant over time, despite not following a predetermined propagation model, it can serve as a stable reference. For instance, in a location close to an AP, if the measured power is consistently reduced due to an obstacle like a wall, this power level remains constant as long as the obstruction remains unchanged. Each point in space is associated with paired values comprising reference point identifiers and unchanging received power levels, forming a unique signature known as a *fingerprint* [69]. However, fingerprinting has notable limitations, including sensitivity to variations in training and testing conditions caused

TABLE II: Comparison of different use cases

Use Case	Location Accuracy	Latency	Description
XR	0.1 m	50 ms	Immersive and interactive systems to improve the learning experience
Holography	1 cm	100 ms	
Indoor Navigation	3 m	1 s	Guidance for finding people/offices within a building or campus
Space Usage and Ocuppancy Tracking	10 m	1 s	Capacity control with DFL systems for safety concerns
Attendance Control	5 m	1 s	To detect the presence whether a student is in a classroom

by dynamic propagation attributes like temperature, humidity, and obstacles [70–72]. It also requires an initial radio map construction phase that limits the covered area, unrecorded data points cannot be used for positioning during operational phases [73].

To address this issue, a commonly used approach is to employ ML algorithms to create an environment model [74–76], which can then be utilized for estimating the position during the exploitation phase. ML algorithms generate a comprehensive model of the scenario through the information provided in the training phase with a reduced number of *fingerprints*. Consequently, the ML models enable a localization service encompassing the entire dessignated area [77, 78].

IV. Localization Technologies for SE

This section explores the radio technologies that are commonly present in educational environments. These technologies are often installed for network access, serving as a backbone for SE services. The purpose of this paper is to present them and define how they can also be opportunistically used for indoor positioning.

A. Cellular Network

Cellular networks offer a myriad of services based on voice and data traffic. Currently, this technology is prevalent in educational institutions as it enables us to access any information source at any time. Many infrastructures are deployed in educational institutions, by operators to handle high densification, and experimental networks by certain universities for research and development purposes.

Although we are at an early stage of 5G deployment, the 3rd Generation Partnership Project (3GPP) has formally declared its commitment to achieving an accuracy of less than 3 meters in both horizontal and vertical dimensions, and up to 10 meters in the vertical plane in open spaces for 80% of the cases 3GPP. To this end, various protocols and techniques will be employed, including the deployment of the multi-Round Trip Time (RTT) protocol [79], which uses timestamps to measure the distance between the UE and the different cells to improve the accuracy of the system. The 3GPP has noted in technical reports, such as [30], that the use of RTT can be effectively employed in both frequency spectrums defined within the 5G framework. These spectrums encompass Frequency Range (FR) 1 for frequencies below 6GHz and FR 2 designed for the millimeter band (mmWave). This protocol will be used in both upstream and downstream communication channel, not only from the serving cell but also from neighboring cells. This approach is aimed of obtaining precise location of users without incurring higher energy costs.

The implementation of 5G operating at high frequencies presents new technical challenges in comparison to lower and mid-band services [80]. Initially, mmWaves have a centimeter-level location precision [81] but a shorter propagation distance, resulting in greater Line-of-Sight (LoS) path loss than sub-6GHz waves, necessitating smaller cell sizes and/or more powerful radio stations [82]. Additionally, mmWaves do not propagate through many of the external/internal building materials such as concrete walls [83, 84]. Despite of being covered, certain fluctuations or areas devoid of connectivity can arise challenges that result in the inconsistent availability of SE services.

It is important to consider the evolving landscape of mobile networks, which are increasingly moving towards the deployment of smaller cellular units. These smaller cells are expected to be highly integrated into SE [10]. The adoption of advanced technologies like beamforming [85] and the densification of cells will allow the presented services in SE. Further network densification results in UEs' receiving greater contextual information, such as distances/angles between APs and UEs, that substantially improves location services, among others. Nonetheless, some cellular network manufacturers have opted for pico-Remote Radio Heads (pRRH) -based infrastructure in industrial deployments. This means that there exist different 5G APs that are operating as a single cell, in a synchronized way. This approach provides several benefits such as the avoidance of handovers between APs when the users are moving. Nevertheless, it makes more difficult to use the 5G APs for localization, since it is not possible to distinguish which AP the user is connected to [86].

B. WiFi

Due to its widespread availability and worldwide deployment, WiFi networks offer global coverage in educational areas that can be the backbone for location-based services within SE. Eduroam is the secure, worldwide roaming access educational network developed for the international research and education, accessible to all students [87]. This network, based on a single shared SSID (Service Set Identifier), has become a standard that selects APs and enables roaming, guaranteeing continuous connectivity while moving between campuses or affiliated institutions [88]. Eduroam stands out for providing a secure worldwide service through the implementation of robust authentication protocols like EAP and WPA2-Enterprise encryption [89].

When WiFi employs the IEEE 802.11mc standard, it incorporates a feature known as Fine Time Measurement (FTM), which facilitates precise distance estimation from the UE to the AP. This estimation is accomplished by the insertion of timestamps and the utilization of the RTT protocol [29, 90]. This release is intended to transform the indoor positioning industry in the coming years, as new smartphones are adopting the IEEE 802.11mc protocol universally [91]. Implementing a 5G network and the necessary infrastructure can be expensive [92], and may not be feasible for all schools or educational institutions. Thus, WiFi technology with eduroam network only needs to change the APs to implement the IEEE 802.11mc protocol to provide an accurate localization service.

The protocol estimates with an accuracy of around one meter the distance of any user that supports the protocol without the need to be connected to the AP [93]. The information is calculated on the UE side to safeguard user privacy, since the location information is not shared among the nodes in the network. Nevertheless, it is also remarkable the extensive study of the conventional WiFi for localization using signal power [68, 94, 95] known as *fingerprinting*.

C. Bluetooth

Bluetooth is an ubiquitous technology owing to its widespread adoption in Personal Area Networks (PANs) such as smartwatches, headphones or smartphones. It is a short-range wireless communications technology which facilitates cost-effective, low-bandwidth, and energy-efficient communication thanks to the BLE protocol [96]. Notably, BLE-based positioning relies on the measurement of signal power as a key determinant [97]. However, this technology offers low precision in localization terms. Under specific LoS conditions and with proximity to APs, an accuracy of only a few meters error can be obtained [98]. Furthermore, BLE holds considerable promise for forthcoming sensor implementations in the Internet of Things (IoT) [99, 100]. Consequently, while Bluetooth technology demonstrates considerable potential, it is not yet as implemented as cellular networks or WiFi in this educational context.

Attendance control via Bluetooth has already been implemented in SE [61]. Despite BLE provides the benefit of broadcasting mode without the requirement for pairing, this characteristic makes BLE vulnerable to passive sniffing attacks [101]. Additionally, BLE has limited coverage; therefore, the most feasible approach for user localisation is fingerprinting, as demonstrated in [61]. However, fingerprinting is a non-scalable technique that necessitates a comprehensive measurement offline phase.

D. Internet of Things (IoT)

A wide range of sensors (e.g. smoke detectors, temperature, and proximity sensors) or beacons (e.g. WiFi or Bluetooth) fall under the category of IoT devices, which play a crucial role in the educational sector as a fundamental enabler [102]. The integration of IoT systems and devices enables multiple applications such as resource monitoring or occupancy tracking [38]. IoT information is typically centralized into a system that cross-correlates data from various IoT enablers to provide localization information [103].

The use of low-cost sensors in IoT allows effective control and monitoring of large areas, contributing to the optimization of spaces and resources. Nevertheless, IoT devices are vulnerable to security breaches that may compromise confidential information and personal privacy [104]. In addition, it is crucial to consider the diversity of the infrastructure across educational institutions, including universities and schools, as well as the resources and advantages afforded by any financial investments made.

The success of a location-based service is largely determined by the chosen educational establishment. It is evident that universities prioritize the allocation of greater resources towards infrastructure technology in comparison to primary or secondary schools. Some universities, such as the University of Malaga, utilise IoT networks that monitor and investigate the effect of vegetation conditions (temperature, humidity, etc.) on students' comfort levels [10]. The University of Zaragoza utilises a spatial and geographic information system to provide ongoing access to the inventory of its facilities and available classrooms [105]. Similarly, the University of Alicante employs a vehicle mobility management system to monitor use of its car parks [106].

E. Computer Vision

Multiple camera-based applications exist for real-time monitoring of educational facilities, such as libraries, cafeterias or classrooms [107]. Furthermore, it is possible to determine levels of occupancy in these spaces using the computer vision, allowing for more efficient use of resources [108].

Image processing constitutes the fundamental element of localization and tracking with computer vision. It provides accurate navigational data which correlates both localization and motion information with centimetric precision [39]. This technology relies on fixed cameras placed at strategic locations within the infrastructure, such as campuses or educational settings. To implement navigation and tracking through the SE needs a map of the building and a configuration phase that involves marking the positions of stationary cameras on the map [109]. The algorithms employed constantly update the navigation status of multiple students based on their current foreground state and previous positions [110]. By examining changes in the image structure, computer vision objectively identifies the foreground elements through pixel correlation [111]. Nevertheless, enlarging the monitored areas results in a significant increase in expense, both in terms of effort and infrastructure, in order to uphold a high level of accuracy.

V. Privacy Concerns

A potential limitation of using localization in SE are the privacy concerns of students. Institutions may need to implement safeguards to ensure that students' location data is not misused [112]. To address these privacy concerns, educational institutions may need to implement strict policies and procedures around the collection and use of location data, as well as a clear and transparent disclosure of these policies.

The General Data Protection Regulation (GDPR) is an European Union (EU) regulation that governs the protection of personal data. In relation to localization privacy, GDPR establishes several requirements for companies that collect, process, and store location data [113]. These requirements include transparency, ensuring that only the minimum amount of data is collected, ensuring that data is accurate and up-to-date, implementing appropriate security measures, limiting data retention and giving individuals the right to access, rectify, and erase their location data [114]. Additionally, GDPR requires institutions to appoint a data protection officer if they process or monitor location data on a large scale or if the core activities of their business involve regular and systematic monitoring of individuals [113].

VI. Proof of Concept

In this section, the PoC is described in full detail. It implements an attendance control system for SE that locates students within a laboratory using cellular technology and WiFi networks, both operating independently and combined. Different techniques for classification and regression are explained, and the different challenges and limitations that this PoC can encounter are defined. In addition, the experiments and the scenario setups are described. Results of the different techniques and technologies are discussed. Finally, a proposal for an architecture that integrates this service within an OpenRAN derived from this PoC is given.

A. Objectives

The main objective consists on localizing the students within a specific classroom depending on their radio signal information for an automatic attendance control system in real-time. To achieve this goal, a comparative analysis is conducted between two different methodologies of Random Forest (RF).

The first approach utilizes a purely classification-based ML model, which determines whether the student is in a laboratory or not based on the provided input. Conversely, the second approach entails a location regression model that estimates the student's position and subsequently classifies whether the student is situated within a laboratory area. Thus, both systems use, as input, the RSSI signal obtained from 5G and WiFi networks working both together and independently. In this case, the system uses RF method that is straightforward to implement and can accomplish high precision in classification and regression processes. The objectives of this PoC are disclosed as follows:

- Performance validation of the automatic attendance control system.
- Comparison of classification and regression success rate.
- Demonstration of the viability and benefits of the opportunistic fusion for location-based services for SE.

B. Methodology

ML techniques enable the prediction of whether the user is inside a classroom. Specifically, RF is used in this PoC because it is a simple technique and can accomplish a high location precision, particularly when used with a significant amount of training data [115]. This technique combines the predictions from various single models, known as *base models*, to create a final outcome. RFs are a versatile tool for a range of ML tasks such as classification, regression or anomaly detection [116]. RFs are particularly effective in classification and regression tasks as they can effectively merge the predictions of multiple decision trees to provide a final location of the UE [117].

RFs create decision trees through a process called bootstrapping, which involves randomly selecting a subset of the training data and using this subset to create a decision tree, this process is repeated multiple times, resulting in a large number of decision trees that are all trained on different subsets of the data [118]. The final prediction is then made by averaging the predictions of all the decision trees in the forest as illustrated in Figure 2. In the case of the classification process, as shown in Figure 2 (a), a majority voting mechanism is employed to determine the final output, which corresponds to the most commonly voted label. In contrast, in the regression model process, depicted in Figure 2 (b), the estimation of the location is achieved by averaging the positions across the trees. RFs are robust to the presence of noise in the data, as the averaging process helps to reduce the impact of any individual decision tree that may be making incorrect predictions [119].

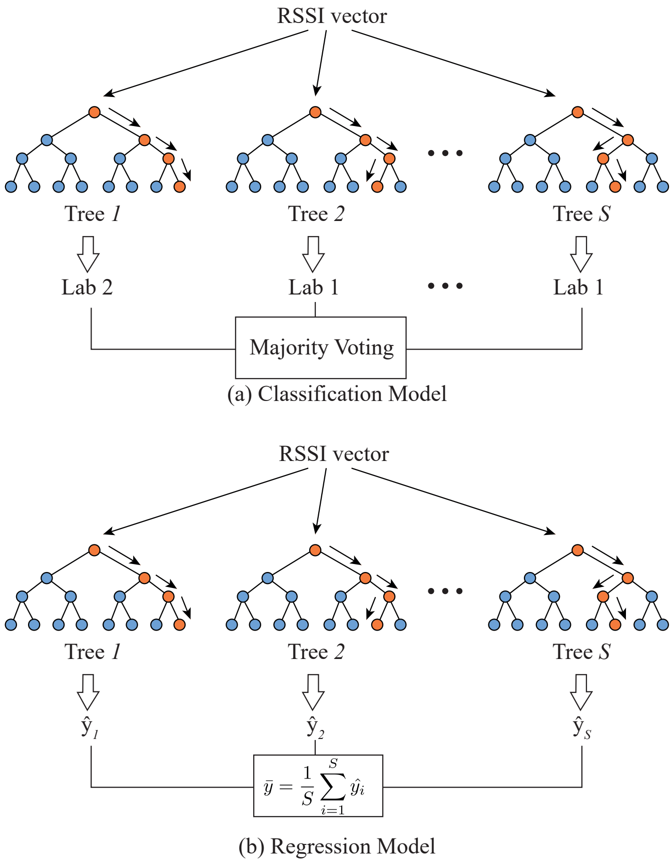

Fig. 2: RF schema

C. Challenges and limitations of the PoC

Due to the high concentration of students within a classroom environment, the personal devices utilized by these students possess the potential to introduce interference within the radio frequency spectrum degrading the end-user position estimation. In addition, areas without coverage may be generated, relying solely on 5G or WiFi localization for attendance control becomes problematic since students may encounter difficulties in establishing network connections.

In this PoC, the focus is on the basic infrastructure commonly found in primary or secondary schools, including cellular networks and WiFi. As a result, this PoC can be conducted at any educational institue with limited resources.

D. Experimental setup

The scenario where the PoC was deployed is located at the University of Malaga and composed by two different laboratories as shown in Figure 3. It is a medium-cluttered scenario with instrumentation equipment that create signal reflections in the whole area. Both 5G and WiFi networks were utilized to conduct the measurement campaign.

Fig. 3: Images of both laboratories

To minimize interference with commercial networks, three gNodeBs (gNBs) were configured for the 5G network, with the stations located at different heights (2.5m and 3.5m), as shown in the map of the scenario map in Figure 4. Additionally, Google WiFi mesh routers were used as WiFi APs, placed on shelves at a height of 2 meters. For the 5G network, the gNBs were placed in the ceiling to provide good visibility and transmit at a frequency of 3774.990 MHz with a power of 20 dBm. The scenario consisted of two laboratories, with an additional laboratory where there is a 5G AP, which included metallic elements that could potentially cause signal blocking, attenuation, and multipath effects. In this study, a dataset comprising more than 250 samples was employed. To facilitate RF training and evaluation, the data was divided into a training set and a testing set, visually depicted in Figure 4 as orange and green dots, respectively. The 20% of the measurements were designated for testing. To ensure reliable statistical outcomes, the experiment was repeated a thousand times, with each iteration involving random selection of training and testing points using the Monte Carlo method. Figure 4 illustrates one instance of this iterative process, ensuring precise statistical results. A Motorola Edge 20 smartphone, operating on Android 11, serves as the target UE for determining location.

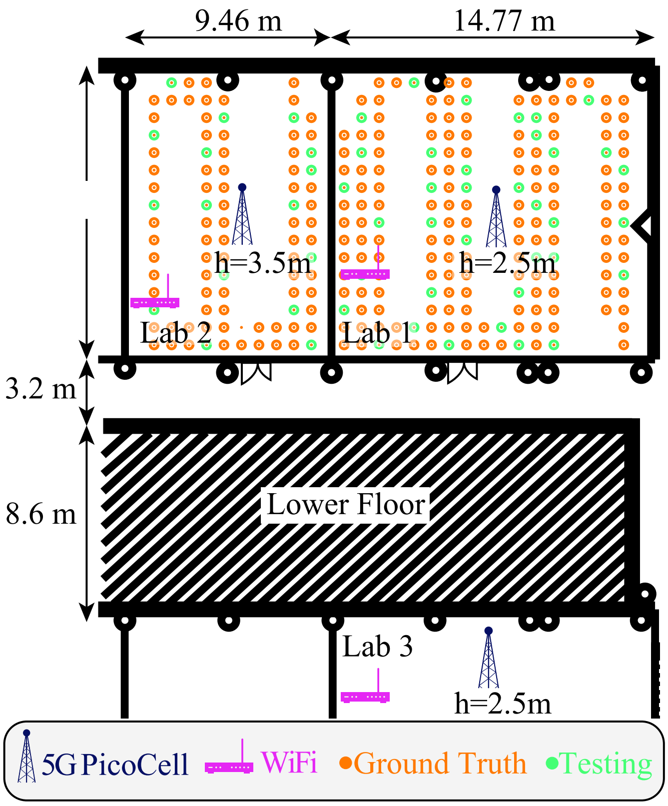

Fig. 4: Map of the scenario

To collect the RSSI of serving and neighboring cells in both 5G and WiFi networks, an smartphone application has been created. The data collected by this application is subsequently transmitted via the 5G network to a server, where the measurement samples are stored in a MySQL database for future analysis. The application also includes a feature for indicating the ground truth location, which is then included along with the measured data. By using this setup and collecting data application from real-world scenarios, we aimed to accurately evaluate the performance of the classification system.

E. Results

This section presents the performance of the localization and classification results achieved from the PoC, which aimed to assess the reliability of the system for classifying a student's location within a specific classroom. To achieve this goal, the performance of both RF models are evaluated by comparing the accuracy of final classification obtained from 5G and WiFi networks, both together and independently.

1) Comparing Accuracy of Classification and Localization-Based Regression Models: in order to assess the effectiveness of the classification and localization-based regression models, it is crucial to compare the accuracy of the classification process in correctly identifying the laboratory where the student is placed. Figure 5 illustrates the percentage of accuracy performance of the classification (orange) and localization-based regression (blue) models for 5G, WiFi, and their fusion.

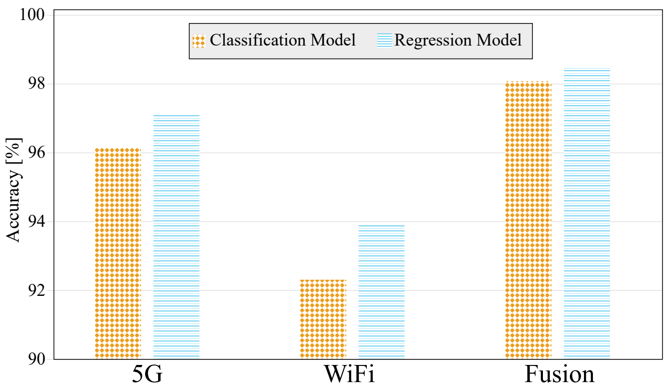

Fig. 5: Comparative accuracy analysis of classification (orange) and regression (blue) RF models for 5G, WiFi and Fusion

The findings demonstrate that the regression model and the fusion of different technologies significantly enhance the overall classification performance of the system. In indoor environments, signal propagation conditions tend to be challenging, resulting in a random reception of RSSI by the UEs due to blockages and multipath effects. Based on the user's position estimation, the system determines whether the user is situated within a classroom. Consequently, in regions closer to the classroom boundaries, there is an enhancement in performance compared to the pure classification method. This enhancement is attributed to the fact that regression systems first estimate the UEs' location and subsequently assign it to a particular classroom.

2) Localization performance by regression: the system classifies the student's location in a specific laboratory. Figure 6 represents the Cumulative Density Function (CDF) of the horizontal localization error. The localization error is relative to the disparity between the estimated final position of the user and the ground truth position. As it can be observed, the performance of 5G (red dotted line) is better than WiFi (blue dashed line). However, the fusion (green line) of both technologies improves the overall performance compared with each technology in isolation. Fusing 5G and WiFi achieves a location error of 5 meters in 80% of the cases, thereby satisfying the location requirements stated in Table II as originally mentioned.

The better precision of the regression, the better performance at the classification process is expected. Notably, when examining the data independently, 5G obtains higher localization precision resulting in a higher accuracy classification results. Consequently, when combining 5G with WiFi data, there is a noticeable enhancement in classification accuracy than in isolation.

By combining two technologies, the system not only improves its classification accuracy but also extends its coverage area beyond what could be achieved with a single technology. Simultaneously employing two supplementary technologies of-

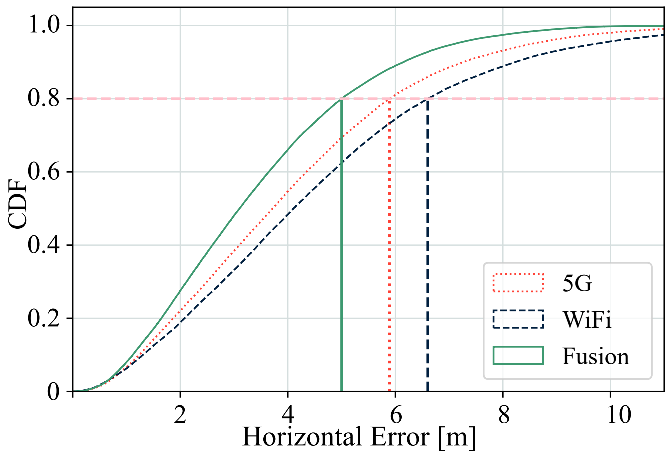

Fig. 6: CDF of localization regression for 5G, WiFi and fusion

fers redundancy in case of system failure or outage, further enhancing the robustness of the system.

VII. Conclusion

Location-based services are increasingly used in education to enhance the learning experience and increase efficiency, with the implementation of XR and indoor navigation on campuses.

This paper aims to provide an overview of localization in SE with real-world examples, analyzing the main technologies and techniques employed to improve the quality of education. After analyzing the challenges and limitations of the different technologies in this educational context, we conducted an experiment on a system created to automate attendance control in education settings with a limited budget. The system effectively demonstrated the advantages of combining various available technologies within educational institutions, as shown by real data.

This PoC illustrates that a localization-based regression model performs better than a simple classifier model. The proposed AAC system can be readily implemented in academic settings, offering a straightforward and unobtrusive method for enhancing teaching and learning efficiency. The attendance monitoring procedure may be executed using students' mobile devices, as all such devices come equipped with both cellular and WiFi technologies. Additionally, the system's data can be analyzed to identify attendance patterns, allowing teachers to optimize class scheduling and delivery. The proposed system streamlines attendance tracking and could provide other location-based services for students, including space usage and occupancy tracking. The potential of wide-spread 5G and WiFi technologies in the education sector to revolutionise how students learn and interact with their surroundings is significant.

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TOPICAL REVIEW

Designing a 6G Testbed for Location: Use Cases, Challenges, Enablers and Requirements

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ABSTRACT Location will have a central role in Research and Development (R&D) towards 6G networks, both as a service offered by the network (improving the current offering of 5G) and as an input to increasingly location-aware services and network functions. To integrate location into 6G standards, it will be very important to design validation systems such as testbeds, even when the actual technology is not yet commercially available. This paper performs a review of the use cases and their requirements, enabling technologies in 6G, and challenges; and proposes a flexible testbed architecture for performing network location related R&D. This architecture will allow to deploy an evolving infrastructure which will allow early validation of 6G technologies.

INDEX TERMS Testbed, proof-of-concept, B5G, 6G, location, positioning.

I. INTRODUCTION

In the last years, as mobile devices have taken the world, location has become a key dimension in communications. New location-aware services are being proposed and deployed, such as localization in emergency cases (floods, fires, earthquakes, etc.) [1], intruder detection [2], Unmanned Autonomous Robots (UAR) navigation [3] or self-driving vehicles. Also, existing procedures of network management are now being enriched with location as a new dimension, such as traffic prediction based on location [4].

Many of these applications cannot rely on traditional Global Navigation Satellite Systems (GNSS). In some cases, they work in indoor environments, where GNSS cannot be used due to lack of satellite visibility. In other cases, energy constraints require that the location is estimated in the network instead of in the device, to save on computational power or the need for additional location circuitry. Some applications also require the network to know the position, which would require the terminals to transmit their location using specific protocols [5](with their associated costs). Therefore, there is a need for network based location estimation [6]. In this case, mobile network infrastructure is used for locating a user instead of satellites, using signal features such as the received power or angle of arrival. The performance of network based location will greatly depend on the capabilities of the underlying network technology.

While 5G is still on an early-stage deployment, studies to foresee how the Sixth Generation (6G) cellular networks will evolve in the next ten years have started, with white papers such as [7] by the European Commission or [8] by the International Telecommunication Union (ITU), and projects such as Hexa-X [9]. 6G will bring better network capabilities than 5G [10], such as throughputs of Tbps [11], latencies below the millisecond [12], very reliable communication (99.9999%) [13] or high-accuracy localization to the centimetre-level [14].

While the grounds for the development of 6G are being settled, there is no unified definition of what such networks will specifically contain. Most authors [15], [16], [17] agree that Artificial Intelligence (AI) and Machine Learning (ML) will play a central role both in the user and control planes, giving place to new applications with ML as a Service (MLaaS) [18], [19], [20] and novel AI/ML-based network management

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schemes. On the architectural level, Network Function Virtualization (NFV) will implement the network elements that support both the user and control planes [21], using Commercial Off-The-Shelf (COTS) hardware and reducing the cost of infrastructure. In this respect, Open Radio Access Networks (Open RAN) [22], [23] is a major breakthrough that is already being used in 5G networks and will continue to be a central feature in 6G, enabling the easy integration of software components from different vendors and speedy creation of new services and functions. Software Defined Networks (SDN [24]) will allow the definition of a dynamic architecture, that can reconfigure the network quickly and adapt it to changes in context (such as changes in traffic, variations in user behaviors, the Deep Network Slicing [17], [25] functionality, the occurrence of catastrophic events, etc.). In this context, 6G will develop a new concept of network operations that will be based on dynamic resource allocation (both in terms of network structure and network functions) for optimizing the general network efficiency [26]. At the physical layer, the migration to higher and wider bands will continue in 6G [27], and new elements, such as smart metasurfaces [2], [28] and massive antenna arrays [29] will enable faster data rates, with a more efficient use of the power. Another important aspect of 6G will be the interoperability [30] with other networks, such as prior 3GPP generations (4/5 G) or non-3GPP technologies (WiFi, LoRA, Sigfox, etc.). While most visions do not consider heterogeneity as a core aspect of 6G, coexistence will be a very important aspect, both as a challenge and as an opportunity.

Several projects have emerged for improving the location accuracy in existing 5G networks up to the meter-level for indoors and outdoors, such as the LOCUS [31] or 5G EVE [32] H2020 projects. With all the aforementioned novelties, 6G will bring a slew of opportunities for better network location. Some authors have already proposed visions of location in 6G [2], [33]. Location will be integrated in basic 6G operation, along with communications [34], [35], [36], thanks to THz frequencies that allow high resolutions for radio-based sensing. Narrower beams [33] will allow to better resolve multipath components for angle-based location. Reconfigurable Intelligent Surfaces (RIS) [2] will also improve location by making the radio environment more predictable. At a higher level, location estimated with these enablers will have its own network function, and will be offered as a service [37]. This service can be offered to applications and network management [38].

While these works reflect on both the enablers for location in 6G (e.g., wideband signals and ML) and location as an enabler of some 6G functions (e.g., context aware management), they do not address an important aspect of development of location technologies in 6G: the infrastructure required for creating proof-of-concepts and evaluating the developed technical components. This aspect is especially relevant at the present time, when development is in the early stages. While simulations are a common way of evaluating location methods [39], the assumptions that are usually done have long been known to add bias to the results [40]. In prior mobile network generations, research on location [41] including testbeds has been done once the core components of the technology were well defined and commercial components were available [42], [43], [44], [45], [46], [47]. Testbeds are often limited to existing commercially available technology and implemented using closed solutions by vendors. Thus, the architecture of the testbed is usually determined by these factors. This limits the type of experiments that can be done to those that the commercial equipment supports, and therefore, there is a need for a well-planned architecture that is defined prior to the acquisition of equipment. This paper proposes a testbed architecture for 6G-based location that can be extended as 6G technologies progress. Since 6G will be the most location-centric of all 3GPP networks yet, it is very important to start this development from the very beginning of the cycle of definition. This will help integrate location and its dependencies (e.g., services to compute location based on measurements or the required signaling) into the early iterations of the first 6G definitions.

This paper will study the task of designing a testbed for location research in 6G. First a review of the uses of location in future 6G-supported applications, its role within the operation of 6G networks and the enablers offered by 6G technologies will be done, highlighting the open research challenges that will need at some point to be studied in a testbed. The requirements and challenges of location will then be explored, identifying which key aspects should be studied in the future and which hardware/software equipment would be needed to evaluate and demonstrate the developed technical components. With these elements, this paper will then propose an architecture for developing location testbeds and review existing implementations for the components of the identified system blocks. Figure 1 summarizes the contribution of this paper.

This paper is organized as follows. In Section II, an overview of existing testbeds will be done, describing some common design principles and relevant implementation aspects. This review will produce two inputs to the design of the architecture, in the form of ideas that can be used in the implementation and challenges that may be present in the process. In Section III, the key use cases are defined, and their requirements in terms of accuracy, latency, and frequency are defined, as well as the main challenges they offer. The review of articles in this section will serve as a source for open research questions that may be answered by experiments done in testbeds. In Section 3, location in 6G is discussed, both reviewing the 6G technologies that are enablers of location, as well as 6G functions that depend on location, both of which must be supported by the proposed architecture, and detailing further open research questions that require evaluation on testbeds. In Section V, a blueprint for a comprehensive testbed will be described, detailing the different required components to evaluate the technologies

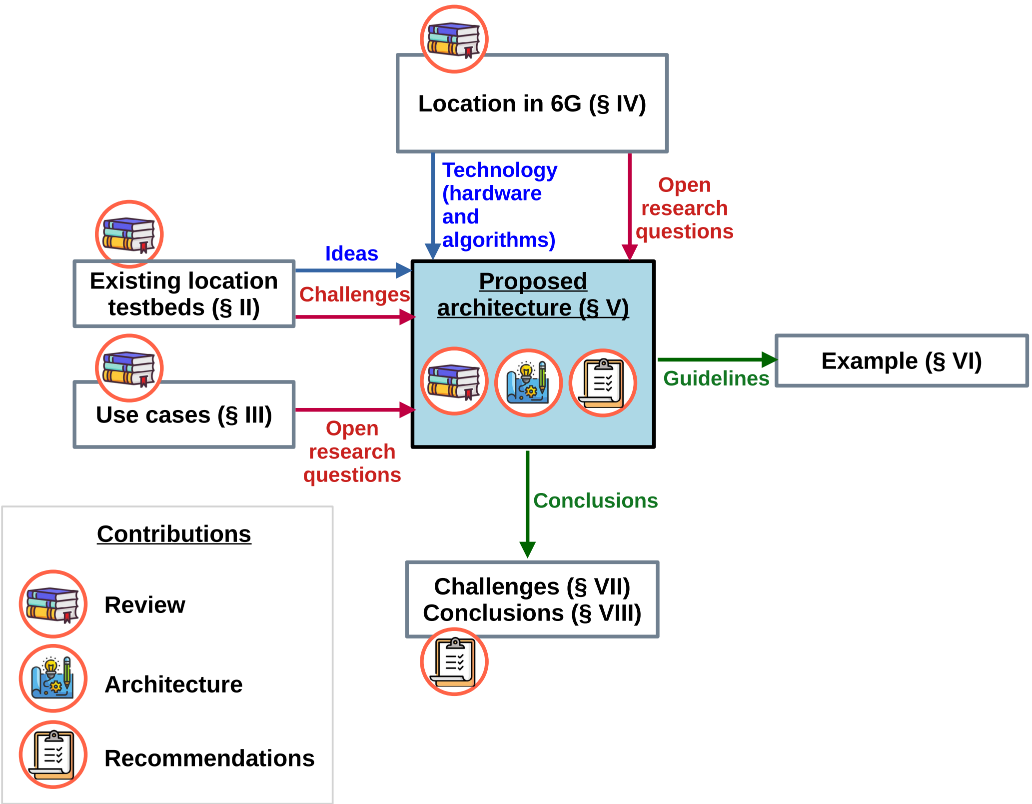

FIGURE 1. Paper organization and contributions.

that will eventually lead to 6G standards. A review of existing technologies that can be used for the implementation is also done in this section, along with recommendations for building a real testbed based on the proposed blueprint. Section VI will describe a real implementation based on the proposed architecture, and which will illustrate how to apply the guidelines. The open challenges for implementation will then be discussed in Section VII, along with recommendations on how to overcome these challenges. Finally, in Section VIII, draws the conclusions of the study.

II. RELATED WORKS

In this section, a brief review of existing location testbeds will be done, pointing out specific particularities and ideas that will be used for the development of the architecture proposed in this paper.

Ultimately, testbeds are used to do proof-of-concepts of pre-existing theoretical development. In location, these development can be either algorithms that provide an estimation for location, or that depend on location as an input. The workflow of research and development of such algorithms goes through several phases, starting with an analytical development, followed normally by simulations and validated through proof-of-concepts in testbeds. Such testbeds can be pre-existing ones, developed with enough flexibility so as to admit experiments on different algorithms; or ad-hoc, specifically designed and deployed for demonstrating an algorithm.

Generic location testbeds [48], [49], [50] are designed to test any location technology, including location algorithms and location-aware services. Such testbeds normally provide a physical space where the experiments take place, a system for providing ground truth (i.e., the actual coordinates of a target, to be used to estimate the error of location algorithms) and a system for collecting data and running experiments. For instance, in [48], an office environment is equipped with elements to perform experiments. Such elements include mobile robots that automate test, equipped with sensors that perform Simultaneous Location and Mapping (SLAM) and which provide a ground truth location. In [50], a factory lab emulates an industrial setting for algorithms used in Industry 4.0 services. In this case, no ground truth is provided, leaving this aspect open for experimental design, but a specific component for deploying experiments and collecting data is described. The *Emulab* testbed [49] provides a generic wireless network testbed, which includes functions for location. A robotic platform is deployed in a large office space, with overhead cameras recording a live video feed with tracking algorithms providing real-time ground truth location. A subsystem to program experiments, collect data, and control everything remotely has also been developed.

Some testbeds are slightly less generic by limiting their scope to specific radio technologies; for instance to WiFi [51] using Received Signal Strength Indicator (RSSI) measurements, or IEEE 802.15.4 [52] with Time of Flight (ToF) measurements. Cellular technologies are well represented in this category, thanks to the growing demand for location based services in mobile networks. For instance, in [43], an experimental Long Term Evolution (LTE) cell is deployed in two different, reconfigurable, indoor scenarios (an empty room and an office setting). It supports ToF and Angle of Arrival (AoA) measurements, and the ground truth is provided by markings on the floor, which are manually fed to the collected data. In [45], a testbed for 5G location is proposed, with robots equipped with SLAM providing ground truth and automation. While it is oriented to 5G, it also supports other technologies, such as WiFi Fine Time Measurement (WiFi-FTM) and vision-based location. The physical setting is in several different indoor areas, including office and open spaces. While there are no location-specific testbeds for 6G, some proposals for generic testbeds are emerging, such as the *Techtile* testbed [53]. In this testbed, tile-based generic radio elements conform an indoor scenario for testing multiple 6G technologies, incluiding mmWave communications and visible light communications. While it is not specifically oriented to location, it has been used for experimenting with ultrasonic and visible light location. It contains a subsystem for collecting data and programming experiments.

Ad-hoc testbeds are developed to demonstrate a specific algorithm. While they lack the flexibility to adapt to different experiments, they are sometimes as complex as generic testbeds, in terms of number and variety of hardware and software elements. The main difference is normally that they lack a programmable component and generic data collection systems that allow experimentation flexibility. For instance, in [54], a testbed for demonstrating a specific range estimation algorithm using wireless networks is demonstrated in a testbed that allows both indoor and outdoor scenarios. In [42], a testbed for demonstrating a location algorithm based on a deep neural network is deployed in two different indoor scenarios (residential and office). A mobile app is developed for taking power measurements of surrounding cell towers and marking ground truth location on a map. In [44], vertical location with cellular networks is tested in a testbed consisting of Software Defined Radio (SDR) base stations and terminals, and compared with Global Positioning System (GPS) and barometer based estimation. In some testbeds in this category, full location is never estimated, but only the elements required for location. For instance, in [46], only AoA measurements of a single terminal and a single 5G base station are taken in an outdoor parking lot, with the purpose of demonstrating a specific network management scheme.

In this paper, a generic architecture for testbeds is proposed in Section V. The proposed architecture provides a blueprint for any type of 6G location testbed, generic (which can be achieved by systematically implementing all the proposed components) or ad-hoc (using the architecture as a generic framework and only implementing the required components for a specific proof-of-concept). A special focus is set on 6G, studying the enabler technologies and new services that it will bring, and exploring the elements that can be procured for a 6G location testbed. This architecture synthesizes the different building blocks of the testbeds cited in this section, along with the experience of the authors in prior work using testbeds. The testbed used in [47] and later expanded to add capabilities and flexibility, is used as an example of the proposed algorithm in Section VI.

A. KEY TAKEOUTS

In this section a quick overview of existing location testbeds has been done. This paper proposes a blueprint for future 6G location testbeds, such that they are implemented following a pre-established plan that responds to the needs of 6G networks and applications. Some ideas that have been proposed in the testbeds reviewed in this section, such as using a ground truth system, or robots for acquiring measurements, can be exported to future 6G testbeds. A clear division between generic and ad-hoc testbeds is also noted, where generic testbeds are implemented to support any experiment in the future, and ad-hoc testbeds to test a specific algorithm or component.

III. KEY USE CASES AND REQUIREMENTS

When development for 5G started, mobile networks were already a commodity, and new services were constantly deployed. But mobile services were no longer limited to end users; around the same time an explosion in Cellular Internet of Things (CIoT [55]) services and applications took place. Thus, 5G was designed not solely as a human-centric network, but also as a CIoT provider. While traditional human-centric applications had more or less simple Key Performance Indicators (KPI) requirements (mainly ever increasing bandwidths for multimedia services) in previous generations, in 5G, requirements had many more dimensions (e.g., reliability, device density, latency, end-to-end quality of service, etc.). Three service categories were defined for 5G [56]:

- Ultra Reliable Low Latency Communications (URLLC): communications with very high reliability (above 99.999%) and very low latency (below 10ms).
- Massive Machine Type Communications (mMTC): services with a very high density of devices (around 1 million devices per km^2).
- Enhanced Mobile Broadband (eMBB): services with very high bandwidth requirements (up to 10Gbps).

These KPIs, which measure the performance of the network, would, on their turn determine the performance of the applications that used the 5G network, which was measured in Service KPIs (SKPIs). The SKPIs were extracted from the use cases that were intended for 5G, and the KPIs that defined the different classes of traffic were derived from there.

Location SKPIs [5] were also defined in 5G, with accuracy (error lower than 50m horizontally and 5m vertically outdoors, and lower than 3m horizontally and vertically for indoors) and location acquisition latency (30 seconds outdoors and 1 second indoors) being the main ones. These requirements were not part of the initial release of 5G (Release 15), but came as an addition in Release 16.

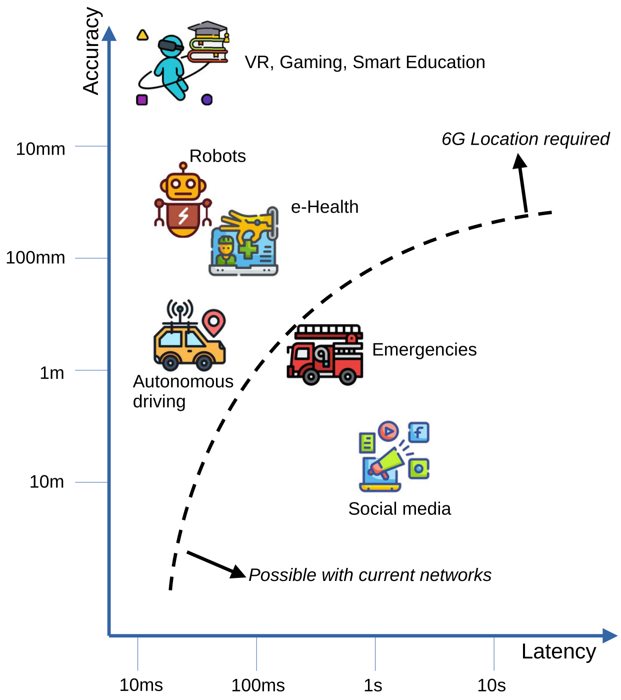

FIGURE 2. **6G use cases and their approximate precision and latency requirements, as described in Section III.**

In 6G, the services that will be supported are more demanding, responding to the decade of technological and social advances that has passed since the inception of the first 5G definition. The SKPI requirements are extreme, requiring performances far superior to those that current 5G technology can provide. From these extreme SKPIs new KPI requirements will be derived, redefining the service categories [57] defined for 5G with traffic that has characteristics that combine requirements of more than one category. In 6G, not only are the required SKPIs higher and the KPI requirements more complex, but networked applications are expected to also have a positive societal impact, measured in Key Societal Value Indicators (KVI [9]), such as the sustainability, trustworthiness, or inclusiveness. Naturally, location SKPIs will also be much more demanding and the applications will have KVI requirements that must be achieved by the network.

In this section, a review of a set of novel use cases for 6G networks that are highly location-dependent will be done, based on a selection of existing reviews of use cases [15], [34], [36], [58]. Figure 2 summarizes these use cases. The dashed line represents the limits of current mobile technology. The requirements for the use cases are detailed in the rest of this section. For each one a brief summary will be given, along with an analysis of the SKPIs (accuracy, latency, and update frequency) and the KVIs (trustworthiness, sustainability, and inclusiveness).

A. SELF DRIVING CARS

As the electric vehicle gains market, the demand for higher security standards grow and drivers seek increasing degrees of comfort. To cover these demands, the development of autonomous driving [59] becomes necessary. Autonomous driving is in the crossroads of several cutting-edge technologies, such as AI/ML [60], [61], advanced sensors [62], URLLC communications [63] and high accuracy location [64]. Autonomous cars interact with different elements of the environment, such as other vehicles, pedestrians, and road signalling. Some of these elements are not equipped with communications equipment, so advanced sensors, such as LiDAR [65], [66] would be required. Others, such as traffic signals, can be equipped with communications elements [67] that interact with the vehicle through wireless Vehicle to Infrastructure (V2I) or Vehicle to Vehicle (V2V) links. With SLAM the vehicle can combine the information of sensors and location providers to predict the trajectory and make decisions in real-time depending on unforeseen events. Some of these decisions cannot be taken with the information available to a single vehicle, such as taking routes to help harmonize traffic, so they must be taken in a centralized element outside of the vehicles [61].

Naturally, location is a major aspect of autonomous driving. Location information is used in many different functions of autonomous driving, such as route planning and tracking [68], course prediction for collision avoidance (with other vehicles, pedestrians, and other obstacles) [65], lane changing [69], fleet management [70], traffic measurement [71], etc. Not all of these applications will have similar requirements; for instance, the accuracy required for traffic measurement is in the tens of meters, while lane changing and course prediction would need sub meter accuracy (along with accurate estimations of speed and acceleration). Regarding localization latency, to provide an accurate prediction of the course, a latency of 100 ms [72] would be required in order to have a margin for reaction in case of potential collisions. Update frequency would depend on aspects such as the cruise speed and the type of road. For instance, in highways, while the speed is high, a relatively low location update frequency would work well for lane estimation, course prediction, etc. In an urban area, or in a parking lot, on the other hand, the geographical features are much smaller, so a high location update rate (up to 10 Hz) would be required.

Location will also have to meet high KVI requirements for autonomous driving. Trustworthiness is the most important aspect in this case. The location provided by the network must be correct and resistant to tampering to avoid possible risky situations and accidents. Privacy, which is another aspect of trustworthiness, must also be preserved, so an attacker cannot gain access to a specific vehicle location [73]. Inclusiveness is a key factor in autonomous driving, in the sense that a higher number of connected vehicles will help the overall functions of autonomous driving work better. In [74], it is shown how a high penetration rate (i.e., proportion of vehicles that can communicate) can drastically reduce traffic congestion. In fact, penetration rate has always been the main challenge in vehicular communications, along with a proper infrastructure connectivity for V2I.

While most of this activity is done outdoors, where advanced GNSS systems can provide a location down to the centimeter [75], some of it takes part either in challenging scenarios like urban canyons [76], [77], in tunnels [78] and in underground parking lots [79] where GNSS is either unavailable or offers a very low accuracy. 6G networks are expected to cover both indoors and outdoors, especially in densely populated areas, so in these scenarios, 6G can be a viable alternative to GNSS (provided it can achieve the SKPI and KVI requirements disclosed earlier and summarized in Table 1). Some studies of 6G connectivity have been done for V2V and V2I [80], but there are currently no studies on location for this use case. A testbed with the appropriate infrastructure (roads, vehicles, signaling elements, etc.) would be required to test network location and V2V and V2I location dependent services.

B. SOCIAL MEDIA

Social media have gained a central role in society in the last years. In the market, there are general social networks (such as Facebook or Twitter) and purpose specific social networks (such as Foursquare, which is centered on location specific data). In many cases, the revenue model of social media services is that of a free service sustained by customized ad delivery. Therefore, there are actually two groups of users of social media: the end users and the entities that use the network for delivering their ads.

Geographic information is becoming an increasingly important data source both for the end user and the ad delivery service [81], [82], [83]. This dependence is more obvious in social media that are built around geographical information, such as Foursquare or Google Maps. Location in social media is used mainly to geotag publications, to offer information about the surroundings of the user and to deliver ads that are relevant to a specific place. All these applications have relatively light requirements, with location accuracies of up to tens of meters [84], [85], several seconds being an acceptable latency and no regular update required (only when interaction with the network occurs).

While the technical requirements may be loose, the KVIs in social networking are the main issue. First of all, trustworthiness is the deciding factor in the usage of social media for many users. Location tracking should be used in benefit of the users, and not to violate their privacy. As per regulations such as General Data Protection Regulation (GDPR) [86], users must be in control of their data, including their location, and must have the ability of fully disabling it. Additionally, the entities that hold location information (e.g., the social network provider or the wireless operator) must also protect it and avoid information leaks [87]. Inclusiveness is also important, since social networks are becoming the main playground for public debate and freedom of speech [88]. Thus, it is important that the location function is available to all users, with a quality that is enough to provide an acceptable social network service.

The open research questions in this use case are mainly centered around the end services, owing to the fact that these use cases are not especially restrictive with location. Detection of bots [89] is a hot topic in social media, where location analysis can play an important role. Finally, the most important challenge in social media is in the privacy of the end users [90], which must be protected from other users and from undesired information leaks to ad networks and malicious actors. As such, a 6G testbed should offer the required functions for testing algorithms for privacy preservation.

C. E-HEALTH

According to the World Health Organization (WHO) [91], healthcare-based devices and facilities can benefit from wireless networks to provide a personalized care. While some development was well underway, the COVID-19 pandemic was a major booster of e-Health technologies [92]. These applications cover different types of monitorization (e.g., smartbands [93]), remote presence applications (remote operation [94] and remote doctor visits [95]) and transportation (ambulance service enhanced with vehicular communications and health sensors [96], or drones for transporting drugs and organs [97]).

Location plays an important role in some of these applications. Some smartbands use location for tracking the movement of users and logging physical activity. Telepresence robots require location for indoor navigation and object manipulation. Drones and ambulances also need location for route planning and navigation. The requirements in terms of SKPIs depend on the scenario. Outdoor applications, such as ambulances, drones, or smartband sports trackers may work with location accuracies of a few meters; while indoor applications, such as telepresence, will normally require sub meter accuracy. Regarding location acquisition latency, the only critical application would be drones, which may face catastrophic consequences if location is not timely (e.g., collision with buildings or other drones). In this case, location sensors should have a maximum latency of 50 ms and a refresh rate of 20 Hz [98].

Health data is considered one of the most sensitive kind of information on individuals, therefore, privacy should be a major priority in all the applications. This is applicable to patient location too. Sustainability will also be a major aspect, since many of the devices will be battery-powered. In order to avoid an increase in chemical waste, and enhance the user friendliness, location (and, in general, wireless technologies in these use cases) should minimize the impact on device power and hence, the need for replacing batteries. Regarding inclusiveness, the health sector strives for covering as much of the population as possible, with an economically viable cost structure. Location technologies must be simple in order to have a low cost.

The convergence of location and communication [36] in 6G will help in the development of low cost devices. Very accurate location and pose estimation of instruments for remote surgery [99] must be investigated and tested. Specifically, whether 6G on its own can provide the required location quality is an open research question, which must be tested as the technology rolls out.

D. EMERGENCY SCENARIOS

In the last years, disaster management has received much attention from the wireless research community, with projects such as the European H2020 RESPOND-A [100] project or government agencies such as the US's Firstnet [101]. This underlines the important role that wireless technologies can eventually have in the work of first responders.

There are numerous tasks in disaster management where location is a key tool. For instance, coordination of first responders [102] is a major issue, requiring that a central command monitors the location of the acting personnel to better manage the resources and avoid hazardous zones. Another important task is to map the disaster area, identifying deviations with respect to the pre-disaster map, and locating hazards such as chemical spills or flammable gases. For such tracking [103], location must have an accuracy of few meters, and latency and frequency of few seconds.

Victim location is another important task, which must be done either by visual inspection, canine units, robots, or by detecting wireless devices [104]. Location in this case must be done again with an accuracy of few meters, so that visual inspection can further determine the exact location and status of the victim. In this case, latency and location update frequency are not too critical, since the victims are not able to move. A higher latency with an accurate location is much better than a quick but imprecise location.

6G and location can be a major enabler of new life-saving protocols, by improving working conditions of first responders and the chances of victims. In this sense, the inclusiveness KVI must measure the survival opportunities of victims in different situations, such as those that are under rubble, or closer to ground zero. Trustworthiness will be measured mainly in the fidelity of the information, for instance, in the first responder command unit (which combines the accuracy in space, the delay of the presented location, and the information of surrounding hazards).

Emergency scenarios are often chaotic and disordered, each having different challenges for first responders, victims, and deployed equipment. For location, the main challenges are the potential lack of infrastructure and the need to communicate and locate victims under rubble. The lack of infrastructure that can be used as reference points for location can be partially solved with portable equipment, such as portable base stations [104] or fusion of technologies [105]. In the case of victims trapped under rubble, location is especially challenging, since rubble acts as heavy clutter for wireless signals [106]. This may greatly affect the vertical location accuracy. In these cases, a dense deployment of reference points, for instance, from heavily sensorized buildings [3], will increase the chances of location.

E. HAPTIC SENSORS AND GAMING

Gaming is one of the fastest growing markets in entertainment in the last years. As gaming propagates among new demographics, the variety in experiences and devices grows. Technologies such as Extended Reality (XR) [107], will enable first-person views in an immersive and interactive experience over digital environments. Within XR, Virtual Reality (VR) provides a fully immersive experience, where the user is completely surrounded by virtual objects and can only interact with them; and Augmented Reality (AR) provides a mixed experience, where the virtual objects interact both with the user and the real environment. While devices like 3D glasses are used for displaying the virtual object, haptic interfaces [108] allow tactile interaction with physical feedback to the user. To quantify the requirements of gaming over mobile networks, a new concept has emerged as Quality-of-Physical-Experience (QoPE) [57] which merges physical aspects from the Quality of Service (QoS) and Quality of Experience (QoE) such as latency and video quality opinion, respectively.

Location plays a key role in XR and haptic interfaces. The user location and body pose are required to compute their view of the virtual objects. An accuracy of 10 cm or less [109] is required to provide a good experience. But most importantly, to avoid dizziness, the user location must be updated with a very low latency (below 20 ms [109]). These requirements can be met by devices that run location and tracking systems, along with 3D rendering, but such devices have a very high cost that hampers the market accessibility to casual users or to users with a lower economic capacity. Cloud gaming [110] solves partially this problem by moving the rendering to the cloud or network edge, but user location must also be sent to the network with a very low latency.

Trustworthiness will be one of the main KVIs for most users, which will need to trust that their privacy is respected within gaming sessions, especially when any kind of economical transaction occurs. Location must therefore be computed and used in a secure manner, ideally within the premises of the network operator (in the network edge). Inclusivity will be achieved mainly by keeping a low cost in the devices, such that they are affordable for all users, all while maintaining a certain QoPE.

5G localization requirements are <3m for 80% of users in indoor deployments [111] which can be considered the main scenario in gaming. Therefore, 6G must overcome the limitations of 5G with extremely low latency and high accuracy location within a challenging indoor scenario.

F. SMART EDUCATION

Education is one of the key pillars of modern society, from very early ages to university education and even mid-career training. As human knowledge advances, the topics that are taught become more and more complex and profound, and the teaching methods must evolve and adapt to new layers of complexity [112], [113]. For this reason, education is a very dynamic market, that adopts not only new teaching methods, but also new technologies. For example, a hot topic nowadays is teaching programming from early ages [114]; and typical blackboard and chalk classes are not an efficient way for this. Instead, in Smart Education methods such as gamification, which relies on transforming the concepts to games and using the dopamine response of the brain to enhance learning, can be used to better engage students. Such gamification methods use technologies like XR or holography [115], which have heavy processing and communications requirements, all while also being physically portable and non-intrusive. These technologies, along with other networked technologies (file sharing, streaming, activity recognition), have requirements which need to be served by 6G infrastructure.

In Smart Education, location plays an important role in several applications. Apart from XR and holography, location is also important in activity recognition. For instance, gesture recognition [116] and location can be used to interact with the AR/VR objects, reducing the complexity (and cost) of the end devices. Sentiment analysis [117] can also be applied to receive a feedback on the learning experience, detecting whether the students are engaging or not in the lessons. The location requirement of activity recognition is similar to that described for gaming, since the basic technologies will be very similar. Location also plays an important role as a feature of the traffic generated by Smart Education applications, which may be used for efficient network management. When students are all located within a classroom [118], broadband traffic will be concentrated in a hotspot served by a few or even just one access point. Such traffic will be similar for all the students, with changes dependent on their exact location (e.g., slightly different viewing angles of the same XR object), so edge resources can be used in a smart manner if the location is known.

Summaryzing, location in Smart Education will mainly have the same requirements as in gaming, XR, and holography, with some particularities on the contents that may be rendered in batches for groups of users that are near each other. All of this must be done under strict privacy and security standards to achieve a high trustworthiness, and a low cost for high inclusivity.

The main challenge is the indoors nature of education, together with the high density of broadband users, which also reflects in high computing power requirements.

G. AUTONOMOUS ROBOTS

Autonomous robots are cyber-physical systems that have the ability of moving around the space without a driver, and have been an important part of the innovations in several markets, such as manufacturing, logistics, first responders, or in wireless networks. Overall, the Autonomous Robotics market [119] is expected to grow 19.6% until 2027, so it will constitute an ever-growing use case for 6G networks.

Autonomous robots may move on a two-dimensional space (when they move on land [120] or over the water [121]), or on a three-dimensional space (in the case of drones [122] or submarines [123]). The accuracy of location depends on the size of the robot and the characteristics of the environment. In the case of open spaces without any obstacles, location will mainly be used for navigation and can have an accuracy of several meters. On the other hand, if location is used in an environment with obstacles such as walls or other robots, narrow corridors, etc. location will also be used for collision avoidance, and the accuracy must then be in the order of centimeters. For instance, cooperative autonomous robots will get centimetre-level localization, from 10cm in industrial scenarios to 50cm for regular consumer cases [34]. Latency and update frequency also depend on what location is used for, as well as the speed of navigation. In the most critical case, the robot must have time to react to the location updates [124]. For instance, drones [98] moving at several meters per second in a dense area should have location updates of themselves and neighboring drones with a frequency of several updates per second (20 Hz), and a latency in the range of tens of milliseconds. Not only location should be provided within these tight margins, but reliability should be very high, avoiding especially situations where several consecutive location updates are missed. Another very important point would be synchronization; to have a correct real-time view of the environment and plan safe trajectories, autonomous robots should be able to coordinate with a correct timing down to the millisecond.

Regarding trustworthiness, it will be more important in scenarios where the robots have critical roles or may cause harm if a wrong location is provided to them. Therefore, location must be provided in a way that it is not possible to falsify the information. Sustainability must also be ensured to improve that battery-powered robots are able to work for a long time without the need for recharging.

Challenges for location also vary depending on the environment. It will be simpler outdoors, where Line of Sight (LOS) is available and the requirements tend to be more loose. Indoors, on the other hand, Non-Line of Sight (NLOS) propagation dominates, making accurate location harder, and the requirements are higher. Indoor scenarios with high clutter will be common in this use case, since robots will be used in scenarios such as factories or distribution centers [125]. A testbed should include the required elements for testing new location algorithms in these scenarios.

H. KEY TAKEOUTS

In this section, a review of 6G-based location has been done, describing each of the use cases, along with the requirements that they have in terms of SKPIs and KVIs. The results of this analysis are summarized in Table 1. A testbed designed to support these use cases or others that are similar, should be able to validate that they comply with the requirements.

IV. LOCATION IN 6G

Location consists of obtaining the coordinates of a *target* in a 2 or 3 dimensional space defined by a *coordinate* or *reference*

TABLE 1. Summary of requirements and challenges of the use cases of 6G location.

	Location requirements (most restrictive)			KVIs	Research challenges
Use Case	Accuracy	Latency	Refresh rate		
Self driving cars	< 1 m	100 ms	10 Hz	Trustworthiness: privacy and tampering avoidance. Inclusiveness: high penetration rate required.	No studies on 6G for vehicular location.
Social media	10 m	5 s	Not required	Trustworthiness: user control, fair use, protection from theft. Inclusiveness: available to all users.	Bot detection, user privacy.
e-Health	< 1 m	50 ms	20 Hz	Trustworthiness: privacy of health data. Sustainability: low power consumption for battery powered devices. Inclusiveness: low cost for equal opportunities.	Remote surgery has very high requirements.
Emergency Scenarios	5 m	Few seconds	Few times per second	Trustworthiness: high fidelity to protect victims and first responders. Inclusiveness: increase survival chances of all victims.	Lack of infrastructure, victims under rubble
Haptic Sensors and Gaming	< 10 cm	< 20 ms	50 Hz	Trustworthiness: data protection. Inclusiveness: low cost.	Very restrictive requirements indoors.
Smart education	< 10 cm	< 20 ms	50 Hz	Trustworthiness: data protection. Inclusiveness: low cost for higher penetration.	Very restrictive requirements indoors, high density of users
Autonomous Robots	10 cm	50 ms	20 Hz	Trustworthiness: security for critical applications. Sustainability: low power consumption for battery powered robots.	Indoor scenarios with high clutter.

system. To obtain the absolute coordinates, the relative position of the target must first be computed with respect to the position of one or more *reference points* whose coordinates are previously known. Several enabling techniques are used for obtaining the relative position information with respect to the reference points and for combining the information to obtain the location.

The obtained coordinate can then be used for location-aware applications, such as those described in Section III. In 6G networks, location will also be used in network functions and network management, making it an integral part of the system.

In this section, the role of 6G networks in location will be reviewed. First, an overview of location techniques will be done in Section IV-A, followed by a review of the enabling technologies in 6G in Section IV-B. Finally, the use of location in 6G functions will be shown in Section IV-C.

A. LOCATION TECHNIQUES

Location techniques obtain an estimation for the location given a set of readings on the reference points. There are several techniques that can be used, depending on the type of available information, computational resources, and performance requirements.

1) LOCATION BY PROXIMITY

The simplest form of location is by proximity of a reference point (Figure 3a). The gross location obtained in this case is equal to the position of the single reference point. The actual estimation is not exactly a single point, but a set of points covering the whole coverage area of the reference point with different degrees of certainty. Points further from the reference point will have a lower certainty, because the probability of detection is reduced with distance. This technique is used, for instance, in Bluetooth Low Energy (BLE) [126], [127], for applications where accuracy is normally not very high.

2) TRILATERATION

A more accurate location can be done with trilateration [105] (Figure 3b). In this case, the data collected from the reference points is the distance or *range*. The range to each reference point defines a circle over which the target may be located. The location is then estimated by the interception of 4 circles (or 3 in 2D location). There are several methods for estimating the range with wireless technology:

- Power-based estimation: this method uses fading to estimate the distance to the reference point. Given a known transmission power, the distance can be obtained by reverting a propagation model. The propagation

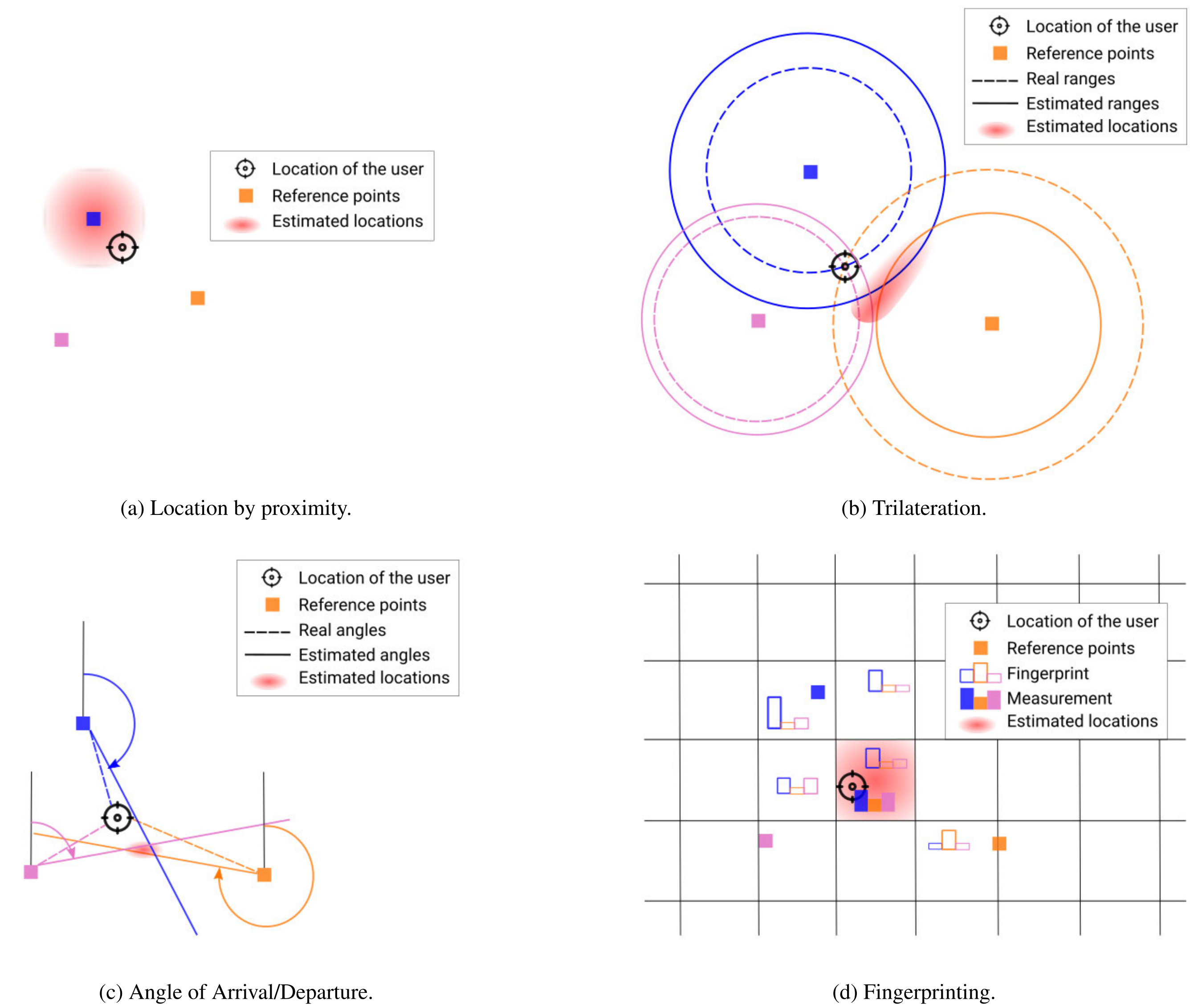

FIGURE 3. Representation of the four main location techniques.

model must be selected taking into consideration the radio technology that is used, the frequency and the environment. For instance, determining whether there is LOS or NLOS [128] is a key aspect to select the model. This method is subject to a high ranging error due to fast fading and multipath propagation. This method has been used in previous mobile network generations [129], [130].

- Time of Flight (ToF) measurements: this method is based on knowing the time that a signal takes to travel through the air between the reference point and the target. The advantage of this method is that it is not affected by fading. Multipath can also be mitigated if the signals are short and there is LOS [131]. Even with NLOS, the accuracy is higher than with power based methods [132]. Direct ToF measurement requires a very tight synchronization between the target and the reference points, making the system very costly. As an alternative, the Round Trip Time (RTT) of the signal can be measured. This is done using a protocol where the signal transmitted by one end is replied by a signal from the other end after a predetermined time. The transmitting end can then estimate the ToF in both directions based solely on its own clock. This is the approach used in technologies such as Ultra Wide Band (UWB [105], [133]) or WiFi Fine Time Measurement (WiFi-FTM), which are capable of achieving cm-level accuracy [105]. ToF has also been tested in 5G [134].
- Time difference of Arrival (TDoA) [135]: RTT requires a protocol between the target and the reference points. An alternative way to calculate distances relying on a single clock is estimating the difference in ToF of a signal between the target and two reference points. This difference can be translated in a difference of distances,

that can be used to define a hyperbola instead of a circle where a user is located. The position can be estimated by the superposition of these hyperbolas instead of circles. This method has also been tested in 5G [136].

Nevertheless, range estimations have errors, and it may happen that the circles or hyperbolas used for trilateration do not cross at a single point or at all, as shown in Figure 3b for 2D location. The actual ranges are represented as dashed lines, while the estimated ranges with errors are shown as full lines. This creates an uncertainty in the location, shown as the red smudge. The darker places of the smudge are those where the confidence for location is higher given the available information. The actual position is not within the smudge, reflecting that there will be an error in this case once the uncertainty is solved. To solve the uncertainty, techniques such as Least Squares (LS) or Weighted Least Squares (WLS) are used.

Trilateration requires a certain density of reference points, such that all the points within the area are covered at least by 4 of them. This can prove challenging, especially in indoor scenarios, where obstacles cause shadowing. Either the density (and hence the cost) must be very high, or the scenario will have coverage holes. One technique that can mitigate this is opportunistic fusion [105], which uses ranges from different technologies. This improves the density by using reference points that are deployed not only for location, but also for wireless communications. This is especially useful in indoor scenarios, where several technologies may coexist; or in emergency situations, where damaged infrastructure can be complemented with low cost and low deployment effort reference points.

3) ANGLE OF ARRIVAL/DEPARTURE

Another magnitude that can be estimated between the reference points and the target is the Angle of Arrival (AoA), which measures the angle at which the signal from the reference points reaches the target, or Angle of Departure (AoD), which measures the angle at which the reference point transmits a signal. These estimations can be done with Multiple Input Multiple Output (MIMO) systems that can either estimate the AoA [137] or that are capable of doing beamforming. Location can be estimated with three AoA or AoD measurements, as shown in Figure 3c. As in the case of trilateration, the error in the estimated angle creates an uncertainty that is solved with LS, WLS, etc.

AoA has been used in 5G [138] achieving sub-meter accuracy in simulations. However, AoA highly suffers from multipath [139]. AoA can also be combined with ToA/TDoA systems [140], combining the advantages of each one.

4) FINGERPRINTING

In indoor scenarios, range estimations can be especially difficult to do and may be prone to large errors. While ToF greatly reduces these errors, it is not always possible to use it, due to the high cost of deploying location-specific radio devices with high density. This is the case, for instance, with WiFi, which is commonly available in indoor scenarios such as offices and residential areas. Moreover, WiFi in such scenarios is densely deployed, with a large number of Access Points (APs) visible to a device at a given point in space.

While the received power may not follow a specific propagation model, if the environment does not change drastically, it tends to remain static over time. For instance, if at a point that is near a WiFi AP the measured power is abnormally low due to an obstacle like a wall, it will not change over time if the obstacle remains static. Thus, each point in space will have a collection of tuples of reference point identifiers (e.g., WiFi Service Set Identifiers) and received powers that do not change over time. These tuples conform a unique signature or *fingerprint* that identifies each point in space. This is the base of fingerprinting (Figure 3d).

Fingerprinting has therefore two steps: a training step, where a map of signatures is collected (normally dividing the map in a fixed size grid), and an exploitation step, where the measured powers are compared with the signatures to obtain the most similar. The highest possible accuracy depends on the size of the grid defined during training. There is a tradeoff between accuracy and complexity, since a fine grid also implies a much longer training step. Fingerprinting can achieve a high accuracy when the density of reference points is high.

Fingerprinting is traditionally associated with WiFi [141], thanks to the high availability of signals in the average residential or office indoor environments. Fingerprinting has been used in mobile networks such as in LTE [142] or 5G [143]. In 6G, the higher densification of base stations will increase the resolution of fingerprinting based location.

While fingerprinting can achieve a high accuracy with low infrastructure investment, it has some major drawbacks. The main one is the need for a complex training, which severely limits the applicability in certain scenarios where prior exploration is not possible or where a large area must be covered. Another important drawback is that on longer timescales the fingerprints may vary (e.g., due to WiFi APs or objects that produce reflections or shadowing being relocated, changes in air humidity, etc.), requiring frequent retrainings of the map.

5) POSE ESTIMATION

Up to this point, techniques that return the location in space have been described; location being a synonym for the vector of coordinates in a specific reference system. This kind of location considers that the target is a single point. Another important magnitude that is often part of the location problem is the pose, which acknowledges that the target is not a single point, but a collection of geometrical shapes that are oriented in specific ways.

There are two approaches to pose estimation that can be combined in different ways. The first one is the estimation of the orientation of an object within the reference system, that is also known as 6D pose estimation [144]. In this case, the three location dimensions are complemented by three orientation

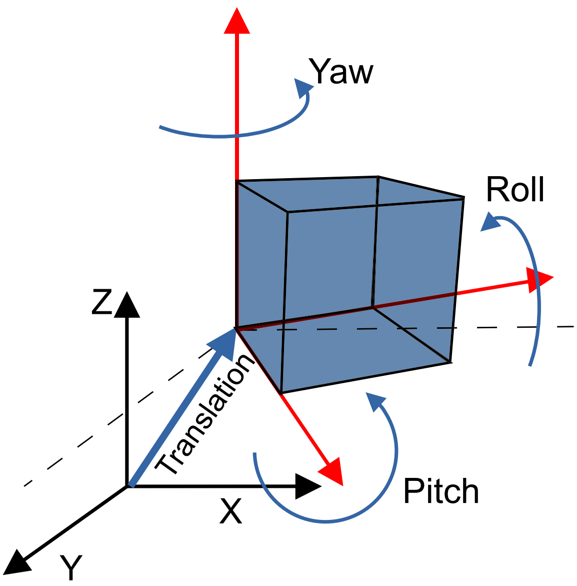

FIGURE 4. 6D pose estimation adds roll, pitch and yaw to the usual cartesian coordinates.

parameters (*roll*, *pitch* and *yaw*, shown in Figure 4). These pose parameters consider a solid object, or define an outline of an object that can be further described by the other pose estimation approach. Wireless technologies have been used for 6D pose estimation; for instance, in [145], a mmWave (24 GHz) radar is used to estimate the pose of mobile robots.

The pose of a non-rigid object can also be defined as the position of its moving parts with respect to each other. The typical example is the estimation of human body pose [146] that allows gesture recognition [116], or even facial recognition [147]. In this case, the problem consists of locating several points of the object with respect to each other, and it can be formulated as the estimation of 3D location of each point with respect to a common reference system. The major challenge in this case is that the accuracy must be very high [148] in situations where the object may interfere with location signals [149].

6) LOCATION FUNCTION PLACEMENT AND PRIVACY

All the location techniques described earlier are agnostic of placement, that is, they can run either in the target or in a network infrastructure that interconnects the reference points (e.g., the 6G network). The placement of the location function will define a set of mechanisms that must be implemented to allow location estimation.

If the location function runs in the target, mechanisms should be in place to inform the target of the location and identification of the reference points. This can be done, for instance, with a predefined map, or with SLAM [150] techniques. In mobile networks, the coordinates of the base station can be transmitted through broadcasting channels, such as the System Information Block; but this has not been done in prior generations. Once the location of the reference points is known, the target needs to know the distances if trilateration is being used. The RTT algorithms used in UWB and WiFi-FTM both allow the device to estimate its own distance to the reference points. For AoA, the terminal must use some type of MIMO technique that allows it to calculate angles. The network may also transmit AoA, AoD, and TDoA measurements to the terminals [151], [152]. In the case of fingerprinting, the device must receive a digital copy of the computed (and updated) map. With these elements, the terminal can estimate its own location, without the need for the network of computing it. This has the drawback of requiring a high computing capacity for this (which may be a problem in IoT devices) and consuming energy at a higher rate. If the network needs the location, a protocol must be established such that the device sends its coordinates to the network. Such a protocol exists, for instance, in LTE, in the LTE Positioning Protocol (LPP [5]).

Location can also be calculated in the network. In this case, a central location service must be defined within the network functions. Such entity would receive range or AoD/AoA estimations to compute the location, either from the reference points or from the targets [151], [152]. If computed in the network, TDoA is calculated at different reference points, and is limited by the synchronization of their clocks [153]. For fingerprinting, a protocol should be established between the target and the location service over which the former can send readings. This relieves the target of the required computational and energetic expenses. If the target needs to know its own position, a client-server protocol must be established with the location service. This is the reasoning behind proposals such as the LOCUS platform [31] for 5G. The recent technical specification group of 3GPP has acknowledged the problem of cellular-based positioning and hybrid combination with non-3GPP technologies [10] in a centralized location service. These new specifications contemplate the possibility of the terminal transmitting measurements such as the ToF, AoA, and the Reference Signal Received Power (RSRP) to the location service.

Since in 6G trustworthiness will be one of the main KVIs, it is important to point out the implications for privacy of the decision on placement. A decentralized scheme where the position is calculated by the target terminal (that is properly secured) will be *private by design* if and only if the network does not participate in the estimation of the ranges. In other words, RTT protocols should not be used, since in that case, the network can also obtain the location of the user and a malicious third party can also intercept such signals. Even in that case, the network will always have a gross location estimation by the technique of the closest reference point (i.e., the serving cell). In the case of a centralized location, privacy is not guaranteed by design [90], and specific countermeasures must be put in place. For instance, the messages interchanged with the location service must be encrypted and anonymized, for instance, with temporary identifiers. In this case, it is up to the operator to follow the personal data management regulations, that, in the case of the GDPR [86] for instance, force them to delete data on request, or protect them from possible leaks.

B. 6G LOCATION ENABLERS

While there is yet no written consensus of what 6G will exactly be, research is ramping up, white papers [2] are suggesting the core components of 6G and research projects with international consortiums have started [9]. Some of these components may be included in earlier, Beyond 5G (B5G) releases, while some may even not make it into the initial release of 6G. As location is an increasingly hot topic in mobile networks and services, it will be an important objective for B5G/6G technologies. In this section, a review of the main technologies that are expected to be part of 6G will be done, based on the visions of papers such as [33], [36], and [107], which explore the relation between 6G and location. For each one, the main aspects that need to be tested in a testbed are explored.

1) HIGHER BANDS AND BANDWIDTHS

The migration to higher bandwidths has been a constant in subsequent mobile network generations, starting from the 30-200 kHz of GSM/GPRS channels [154] to up to 800 MHz in Frequency Range 2 (FR2) in 5G [155]. In 6G, channel bandwidths will further increase up to 2-10 GHz per channel in the THz band [34]. To achieve this, higher carrier frequencies shall be used. While in 5G one of the main novelties was the introduction of FR2 (also known as mmWave), in 6G, frequencies above 100 GHz (also known as μmWave) [2] or even in the THz band [16] are envisioned.

This brings two main advantages with regards to location; firstly, higher bandwidths have much lower beam widths [2], which coupled with beamforming, can lead to very accurate angle estimations; and secondly, large bandwidths allow very short signals, which can be used for better discarding multipath [156] components in time (similar to UWB [133], [157], [158]). On the other hand, atmospheric absorption is much higher at such high frequencies, leading to small ranges and the need of Line-of-Sight propagation.

These new features of 6G are a natural evolution of the physical layer of 5G; and as such, these benefits on location were already observed in 5G with respect to prior generations. In other words, mmWave also offered an increased directionality [159] and allowed ToF measurements, although not with the accuracy expected from μmWave. To evaluate the exact benefits of μmWave in location, several different aspects must be measured. Firstly, the achievable directionality, which will provide a specific angular accuracy must be measured. Secondly, the ToF resolution must be assessed, which will depend on the shortest achievable pulse and the atmospheric effects, which are much more relevant at higher frequencies. The required 6G RTT protocols must also be designed and tested.

2) VIRTUALIZATION AND OPEN RAN

The architecture of the mobile network has changed throughout the different generations. While in 2G and 3G network functions were tightly associated to specific inflexible

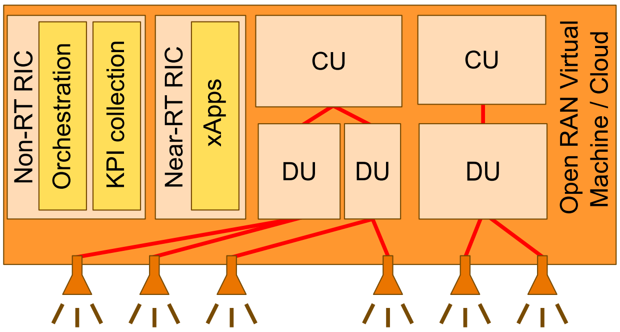

FIGURE 5. Open RAN architecture, where all functions are virtual and SDRs perform the physical radio functions.

elements, in 4G there was a simplification in the architecture [160]; and in 5G the introduction of SDN [161] and Open RAN [22], [23] simplified the implementation of the core network with COTS hardware and even cloud-based virtual machines. In 6G, this trend towards virtual machines continues. Network functions are implemented as microservices that can be containerized with technologies such as Docker [162], [163], [164], [165] or Kernel-based Virtual Machines (KVM) [163], [166], deployed in the cloud and orchestrated with scalable solutions such as Kubernetes [167] or OpenStack [168]. This approach will define a network infrastructure that is essentially a set of microservices that need a certain organization. Open RAN [169] defines a standardized architecture (Figure 5) that allows interoperability between components developed by different vendors. The main component elements are:

- Distributed Unit (DU): contains the lower layers of a traditional base station (Physical layer, Medium Access Control, and Radio Link Control).
- Control Unit (CU): contains the higher layers of a base station. A single CU can have numerous DUs distributed over a wide area.
- Near Real-Time Radio Intelligent Controller (RT-RIC): will contain the network functions that are time sensitive, such as mobility management, security, etc.
- Service Management and Orchestration Framework: containing the network management functions (in the Non-RT-RIC), configuration, policies, etc.

An important aspect of this architecture is its openness, which adds flexibility to the composition of the network, allowing the integration of new and more efficient implementations of network functions, which can be developed and distributed by small and specialized vendors. These software components are called *xApps*, and will give place to a market of competing solutions for low level functions in the 6G network. This will also greatly simplify the inclusion of new network functions and reduce the time-to-market of novel schemes developed in the research community.

Open RAN greatly simplifies the integration of location in the network operation. Access to information of the CU can help obtain physical layer measurements (such as Timing Advance, ToA, or AoA) taken at the DU. Furthermore, access to information from several DUs can enable trilateration within a single CU. This can be done either passively (by having an xApp that collects data and derives distances to DU antennas) or actively (by having the DUs communicating with the terminal in order to estimate the distance with protocols such as RTT). Thanks to the tight integration offered by the Near-RT-RIC, this will produce location latencies that are very low, and will also allow for high frequency location updates.

Many questions remain open, such as whether a location xApp will have in practice a negative impact over the performance of a CU, which is translated into lower quality of service. To measure this, the memory and processing time of different location algorithms and protocols should be measured within an Open RAN architecture.

3) DENSIFICATION AND CELL-FREE ARCHITECTURE

Another aspect that has constantly increased with each generation of mobile networks is the densification of base stations. This is a direct consequence of migration to higher frequencies and bandwidths. As higher frequencies are used, path loss also increases, driving to a need of either a higher transmission power or a lower cell radius. Lower cell radii also imply a lower number of users per cell, which allows for higher bandwidth and more resources per user. Regarding cell radius, there are macrocells (with coverages up to several km), small cells (with up to 100m) and femtocells (which cover the area of a home or small office). For 6G, the concept of cells is expected to be changed [11], [17], [170]. DUs are much simpler (and therefore, cheaper) and flexible than base stations, and can be added and removed with much less effort, allowing for a scalable network. Additionally, DUs may even be mounted on mobile platforms, to provide temporary connectivity for IoT [171] or disaster scenarios [172] using, for instance, Unmanned Aerial Vehicles (UAV).

Regarding location, DUs can act as reference points, and as they will be packed more densely, it is expected that the terminals will have more location information available. Also, the smaller size of the coverage area of one DU will provide a finer location by proximity. In addition, UAV-mounted DUs may improve location by increasing the density temporarily when needed [173] (e.g., in emergencies or special events).

To characterize the advantages of the cell-free architecture of 6G, a measurement of the time required to coordinate several DUs must be obtained, as well as an exploration of the potential pitfalls (such as a target only being visible to less than 3 DUs) and solutions that can be proposed. Regarding densification, the tradeoff between a lower intercell distance and higher path loss must be evaluated. The higher DU density also may favor the usage of fingerprinting, so measurements that also characterize this aspect (e.g., map of visible DUs over an area) could also be of great value.

4) AI AND ML AS ENABLERS OF LOCATION

One of the most cited novelties of 6G are the increased integration with AI and ML [17], [174]. There are three roles that AI/ML will be used for in 6G: running network functions, network management, and to be offered as a service for user applications (MLaaS) [18], [19], [20]. To support these roles, some works suggest the use of a specific AI/ML component within the network, such that all the computing resources (hardware accelerators, storage, software libraries, etc.) are centralized in a single point. This will allow to better dimension and capitalize the dedicated resources. Such a component would centralize all the datasets and models used in the above mentioned functions. Nevertheless, this can be problematic for some cases. For instance, to protect privacy, some datasets may not be acquired and stored for long terms, so schemes such as federated learning [175], [176] have also been proposed for 6G services and functions. In federated learning, several nodes perform ML on their own datasets, and share the resulting model, which theoretically does not have sensitive information. The applications of AI/ML for the operation of the network are further explained in Section IV-C. Cloud-based AI/ML services constitute a novel and active market [19]. Mobile network operators have an edge over other providers for offering such services. Firstly, they can offer services that are much closer to the end users, located within the CU, with much lower latency for data transmission. Secondly, they can reuse hardware (such as hardware AI/ML accelerators) and software (such as specific algorithms or pre-trained models) components that are already being used for network functions and orchestration.

AI/ML as a service offered by the 6G network can be used as an enabler of location. Location with soft information [177] is a clear example of this. Some AI/ML techniques can help improve location accuracy; for instance, Kalman Filters [178] are commonly used to improve location through fusion with Inertial Motion Unit (IMU) data [179], and LOS/NLOS conditions can be estimated with ML [180] to improve ranging information. Source weighting based on accuracy has also shown improvements in location accuracy [105].

In the near future, there will be many aspects of AI/ML to evaluate towards 6G in real testbeds. Aspects such as dataset sizes, computing performance (in terms of memory and processor time) and learning and estimation times will all determine the location acquisition latency, frequency, and accuracy when AI/ML is an enabler of location.

5) EDGE COMPUTING

In 5G, one of the key technologies for achieving low latencies was Edge Computing [181], where the end-to-end services were "moved" to the network edge. This was possible thanks to cloud computing technologies [182], where a service can be disaggregated into several servers which share information over a backhaul connection. In 6G, this trend continues, with more sophisticated Edge Computing schemes such as federated learning [175]; and the addition of xApps allows a cross-layer integration between end-to-end services and the CU/DU.

While location already benefits from Edge Computing in 5G [183], [184], the integration with CU/DU can further enhance location accuracy, for instance, by connecting it with external data services that allow context awareness (e.g., by integrating geographical Application Programming Interfaces -APIs- in the estimation of distances with physical magnitudes). This can be done without significantly increasing location acquisition latency.

To explore the integration of Edge Computing into 6G and location, several research questions remain open. For instance, instantiating Edge services implies some delay [185], so the impact of this delay should be further investigated and solutions developed to overcome this problem. One potential solution would be the predictive instantiation based on context awareness [186], [187]. Furthermore, the procurement of computing resources in the Edge (in terms of memory and computing power) is also an open research question, which has some precedents in 5G, for instance for task offloading from the terminals [188], [189]. In 6G, other uses, such as federated learning [190] will also require a careful resource planning in the Edge.

6) COEXISTENCE WITH OTHER NETWORKS

As mobile network generations have progressed, backwards compatibility has not been maintained. This has driven to devices and networks where radio interfaces for several generations, ranging from 2G to 5G are present simultaneously. Given the inertia of older generations, it is very likely that in 6G, several 3GPP technologies coexist in the same network [30]. Moreover, other radio technologies are also present in the same spaces than mobile networks, such as WiFi, LoraWAN [191], Bluetooth, etc. Coexistence with older generations and other radio technologies has been a widely studied issue in prior generations, leading to the development of schemes such as Listen Before Talk (LBT) in 5G non-licensed spectrum bands [192]. While coexistence with other technologies is an important challenge, synergies have also been exploited for improving the quality of service. Inter-technology handovers [193] can be used to handoff traffic to Radio Access Networks (RANs) of different 3GPP Releases, for instance, when an imbalance in traffic is detected or when a user exits the coverage area of the newer generation. Inter-technology synergy has also been proposed with non-3GPP technologies, for instance, with optical networks [194], WiFi [195], capillary networks [196] or LoRaWAN [191].

Location can greatly benefit from the coexistence of several RAN technologies. Technologies such as UWB [133] and WiFi-FTM [197] are currently competing in the market of indoor location. Both of these technologies use a flavor of the RTT protocol to estimate the distance to the reference points. UWB has been a de-facto standard for indoor location for a long time, and is now starting to acquire a significant market share in consumer devices [198]. WiFi-FTM [105], [199] is more recent and is part of IEEE 802.11mc, so it has a great potential of adoption by consumer devices, especially because it can provide location without the need of connecting to an access point [200]. Both of these technologies offer local coverage, and can complement mobile network based location indoors, with techniques such as range fusion [47], [105]. Other location technologies such as WiFi fingerprinting [141], GNSS [140], [201] (which is already integrated with LTE through LPP [5] and in 5G through New Radio Positioning Protocol A -NRPPa [202]), GNSS with Real-Time Kinematics (RTK) [203], Bluetooth proximity [126], [127] or SigFox [204] can also be used to improve future 6G location. Thanks to mechanisms such as Kalman Filters, readings from sensors in devices (such as IMUs) or even from sensing functions of 6G (e.g., passive RADAR [36]) can also be used to improve location while tracking a specific user.

6G location can be complemented with the aforementioned technologies, either to improve accuracy (for instance, by using fusion with UWB), latency, or update frequency (e.g., with Kalman Filters). Another important aspect that can be improved is availability of location. As described in Section III-B, at least 4 ranges are required for 3D location. But it is possible that at some points in space (especially in indoor spaces), there are less than 4 visible CUs. In that case, complementing with other technologies opportunistically [105] can improve the chances of acquiring location. The exact improvements that can be obtained will depend on environmental aspects such as topography of the surroundings, available networks, density of CUs and reference points of other technologies, etc.; and will come at a cost that also has to be measured in a testbed, mainly in terms of excess of power consumption (in the network due to the deployment of other RANs and in the terminals due to the activity of more network interfaces) and computational resources.

7) SMART METASURFACES

In traditional mobile communications, reflections are usually considered random and uncontrollable. Reflections are sometimes considered a negative effect that causes scattering and needs to be mitigated. On the other hand, reflections are also used for NLOS communications. With smart metasurfaces [28], [205], the reflections can be strategically modulated to improve the propagation conditions. Smart metasurfaces are made up of nanostructures and metamaterials that can shape the electromagnetic properties of the surface (such as its reflectivity, selectivity to frequencies and polarization, etc.).

Regarding location, smart metasurfaces can improve location in interiors, where NLOS conditions are dominant, for instance, exploiting near-field effects [36].

Smart metasurfaces are a cutting edge technology, where much research and development must still be done and major challenges overcome. For instance, a major question when using smart metasurfaces is where to install them [206] in order to obtain the best results. The physical characteristics of the materials are also an open research question [207], as well as the propagation models with materials with different sets of characteristics [208].

8) MASSIVE MIMO

In Massive MIMO (mMIMO), devices have many antennas (up to millions of elements [16]), to allow for different kinds of connectivity improvement. mMIMO has been used in 5G for beamforming [209] allowing very narrow and quickly reconfigurable beams, spatial multiplexing to increase the capacity of individual users, increased diversity gain [210] to achieve a higher reliability and to estimate the AoA in communications [138]. In 6G, with THz frequencies, mMIMO antennas can be very small [211], using advanced fabrication processes with metamaterials.

mMIMO offers some interesting elements for location systems. AoA estimation is an obvious location enabler, as previously discussed in Section III-C. In 6G, thanks to a higher number of antennas, these estimations may be much more accurate. Furthermore, the use of THz arrays will allow the use of personal radars [2], which can create radio images from the surrounding environments, for applications such as SLAM.

To further investigate these technologies, testbed measurements should include mMIMO antennas and transceivers. Aspects such as spatial and angular resolutions need to be assessed in order to establish the location accuracy that can be achieved. Moreover, some other practical aspects still need to be studied, such as the power consumption, or the reliability of personal radars in different scenarios (for instance, whether the user of the device needs to proactively interact with the device to obtain a radio map of the environment).

9) D2D

In mobile networks, terminals usually connect to a single serving base station. As new releases have arrived, this original scheme has been modified adding alternative configurations such as multiconnectivity [212] and Device To Device (D2D [213]) to the 3GPP standards. D2D allows terminals to directly communicate among each other. D2D communications can help save energy [214] when Peer-to-Peer (P2P) services are running within a small geographical area. In this case, terminals that are within the local area can use a much lower transmission power to reach nearby terminals, instead of a distant base station. D2D can also be used for extending the coverage of the mobile network [215], using terminals as relays of the base station to serve other nearby terminals that are out of coverage due to obstacles. In 6G [216], all the technical improvements, such as AI/ML, Edge Computing, novel architecture, etc. will enhance D2D communications.

D2D can be used for cooperative location [156], where terminals use the signals from other terminals (either passively or actively) to estimate distances for trilateration or fingerprinting. This is especially useful in situations where some terminals are not within the coverage area of a fixed reference point.

D2D helps in situations where coverage is problematic, both for communications and location. However, these situations tend to occur when the propagation conditions are harsh, for instance, in underground or industrial settings. In these situations, while D2D would potentially improve the chances of having enough distance measurements for location, these distances will likely be inaccurate, since they also depend on the quality of the channel. To assess the usefulness of D2D for location in 6G, a study of the accuracy in real situations must be done, as well as the achievable improvement on reliability (in other words, the improvement of the chances of measuring enough reference points).

C. 6G LOCATION-DEPENDENT FUNCTIONALITY

While 6G provides many enablers for new and improved location functions, as shown in the previous section, it is also the most location-dependent mobile generation so far. Several of potential B5G and 6G technologies will heavily rely on location information. The design and testing process of these technologies will require in the near future a testbed with location capabilities that mimic those expected for 6G. These location-dependent functionalities will be described in this section, along with the general requirements they impose on the location service.

1) RAN FUNCTIONS

Mobile networks operation relies on a complex set of individual functions in the RAN. For instance, handovers in their different flavors (soft, softer, and hard) and cell reselection are the basis of mobility from the very early 3GPP releases, complemented with more advanced functions such as beam selection and secondary cell selection for multiconnectivity. Other RAN functions are not directly related with mobility, but with traffic management, for instance, traffic steering or admission control. In recent years, these functions have been complemented with AI/ML techniques to make them proactive. For instance, in [125], schemes for adjusting network slice resources in different scenarios are proposed, based on predictors of traffic composition. In 6G, as most of the functions of the RAN tend to be virtualized, management can be much more flexible, allowing not only to adjust radio resources, but also computational resources [217]. In fact, Open RAN will greatly augment the possibilities of management in the releases leading to 6G [218].

Location will play a major role in network functions in 6G. For instance, resources can be dynamically assigned to DUs and specific beams in function of the projected aggregated location of the users in the network. This will allow to do a more efficient usage of resources.

For these functions, location will need to meet some specifications that depend on the specific function and the service that is being provided. For instance, in multiconnectivity for URLLC, the selection of new secondary base stations or the change of beams must be done in a short period, so the terminal never loses network connectivity. Location latency will then need to be very low (in the order of few ms) to ensure a correct assignment of resources. Regarding accuracy, it will depend on the size of the radio features (coverage area, beam width, etc.) that a specific function covers.

2) NETWORK MANAGEMENT

Network management comprises the configuration, optimization, and troubleshooting of RAN and core network functions. As mobile networks have become more complex, automation of network management has become an increasing necessity. In the last years, many different solutions, ranging from very specific management problems [125], [206], [219] to whole Self-Organized Network (SON) architectures [220], [221], [222] based on AI/ML and Big Data analytics, have been proposed. Such proposals respond to the increase in complexity of network management due to, among others, the coexistence of different RANs (2/3/4/5G, WiFi, LPWANs). In 6G, AI/ML will be an integral part of the core network, and it is expected that management automation relies heavily on it [223], enabling intent-based management, which translates business requirements into specific network parameter configurations. Open RAN will increase the complexity of management, but will also increase the range of possible operations that can be done without human intervention (such as adding or subtracting computing infrastructure). Network optimization is normally done offline, that is, it is a long term task that continuously monitors the network state and implements gradually a fine tuning of network functions. While it is not temporally sensitive, automatic optimization cannot take too long to adapt the resources to changes of the environment or traffic. For instance, for human-centric services, the permissible timeframes have been reduced from several days in early network generations to several minutes in 5G. Regarding troubleshooting, automation must fulfill four tasks [221]: detection of the problem and definition of which network elements are affected, compensation (i.e., redirection of redundant equipment in the network to serve the affected users), diagnosis or root cause analysis, and resolution. The time frame of troubleshooting depends on the type of failure, ranging from low priority ones (such as cells having non-optimal configuration parameters) which can be observed for several days before being resolved, to critical ones (such as coverage holes in areas with URLLC terminals), which must be corrected proactively, before users are affected.

Location will be a key resource for many management functions. Both radio resources (such as bandwidth or radiated power) and computing resources (memory, compute time, and priority of virtual functions) can be proactively redistributed among different DUs in function of where the users are concentrated or where they are moving. Moreover, configuration can be done taking into account specific users with critical requirements, helping to optimize the network for them. Location can also be an invaluable resource for troubleshooting; for instance to locate coverage holes or inefficiencies in beam parameters.

The requirements imposed over the location service will vary with the specific management function. For instance, for a CU to proactively optimize the resources (radio and computing) of several DUs, the aggregated location of users must be calculated with a delay in the order of tens of seconds to few minutes for end-user communications. Above this, users may notice some effects derived from resource scarcity. Nevertheless, if the DUs are serving traffic with high performance requirements, it is possible that the resource management must be done in much shorter periods (tens of ms) to ensure that the terminals will have resources when needed. In this case, location must be calculated with a latency in the order of few ms. In any case, this low latency would only be required for critical terminals or for terminals that are moving very fast.

3) COMPUTATIONAL RESOURCE PLACEMENT

With Open RAN, network elements are virtualized, containerized, and run over COTS computers with diverse platform architectures, operating systems, resources, and placements (i.e., the location of the physical computer running the virtual image). A single instance of a specific function (e.g., a CU) can even run on a distributed cloud, having parts of it run over different physical machines. This adds some new dimensions to the mobile network management: computing power (in terms of processing capacity), memory and storage space, energy consumption, and placement. Placement is especially relevant in time-sensitive applications where the additional latency introduced by the backbone network in higher layer functions (e.g., authentication) is not affordable. In 6G, thanks to Open RAN and virtualization, placement has a more profound influence than in prior generations, since not only the end services can be moved to the edge (as in 5G), but also RAN and core network functions [224], [225].

To successfully exploit the capability of changing the placement of network functions in 6G, the key aspect to know about the users is their location. Similarly to management, only the location of users that have special needs must be known. With this information, virtualized functions can be moved near the users cutting the latency introduced by the network. Furthermore, with trajectory analysis, a proactive placement of the functions can be done.

In the case of placement of resources, the required location is coarse, not needing an accuracy that is much higher than the service area of a DU. Nevertheless, for more sophisticated mechanisms, such as proactive placement based on trajectory analysis, a higher accuracy may be required, down to several meters. To test such mechanisms, a testbed should have the capability of dynamically placing functions within a representative area, and measuring KPIs such as reduction in latency due to a correct placement or proportion of incorrect placements in proactive placement.

4) CONTEXT AWARENESS

Mobile networks exist within a context [226] that directly affects them in several ways. Some of the most obvious contextual factors are external interference, and traffic patterns due to events that occur within the coverage area of the network, such as social events [227], disasters (which may also damage the network infrastructure) or user mobility patterns [177]. On a smaller scale, the radioelectric environment may also change, for instance, within a small area the passage of cars, or opening/closing doors may modify the LOS/NLOS conditions. The knowledge of these contextual factors will allow to better plan networks, perform proactive management and placement of functions.

Location of users with respect to network infrastructure is a very important contextual factor. It may define not only LOS/NLOS conditions of individual users, but also mobility patterns of the users as a whole [177]. This information is important for context aware functionality, such as context-aware network management or physical layer configuration. For location aware functionality, the accuracy and latency required for the location will highly depend on the specific function. For instance, in high-level network management, aggregation of locations will somehow reduce the impact of individual errors, so a low accuracy (of up to tens of meters) is acceptable. LOS/NLOS detection, on the other hand, may have a much less permissive accuracy requirement, especially in indoor scenarios, where conditions change in sub-meter scales.

To test such functions in a testbed, magnitudes such as the sensitivity to location errors and latency must be measured. Another important aspect is the rate of users that are reporting location. Since not all users may be located (due to device capabilities or privacy options), it may happen that only a sample of the users are located, so the representativeness of such sample will determine the performance of location aware network functions.

5) LOCATION AS ENABLER OF AI AND ML

As earlier described in Section IV-B, AI and ML can be used as enablers for location. Conversely, location can be used as an input for location-aware models in AI/ML. In prior mobile network generations, AI/ML have been proposed for several network functionalities and management mechanisms. The concept of SON, which was proposed back when 3G was rolling out, relies heavily on AI/ML for tasks such as troubleshooting and parameter optimization. In 4G, SON functions were also proposed [221], and some of them, such as Automatic Neighbor Relation (ANR) were even part of the 3GPP standard [228]. As the research on 5G is still ongoing, AI/ML solutions to common problems abound, especially to manage complex functions such as Network Slicing [56], [125]. With 6G, the use of more sophisticated AI/ML systems are expected. There are three roles that AI/ML will take in 6G:

- AI/ML for running network functions: some common functions, such as resource assignment [217], traffic steering [229] or security [230] will be implemented with AI/ML algorithms that make them predictive and adaptable to the changes in the environment. These functions will be part of the Near-RT-RIC and distributed as xApps.
- AI/ML for network management: AI/ML algorithms will also be used for network orchestration functions in the Non-RT-RIC. Research is ongoing for orchestration tasks such as network optimization [231], while others, like troubleshooting, have not yet received much attention.
- AI/ML as a service: as already explained in Section IV-B.

For all of these functions, location can be used as an input in AI/ML algorithms. Location information has been used for tasks such as network orchestration [177] or virtual function placement [186], [187].

When location is the enabler of other functions and services, the problem to study is whether its performance meets the requirements. Moreover, dataset security must also be explored, evaluating risks such as model inversion [230] or dataset poisoning [20].

D. KEY TAKEOUTS

In this section, the location topics related with 6G have been reviewed.

First, a short review of location techniques was done, showing the type of algorithms that run in the devices that are tested in a location testbed. This will, in its turn, define which elements must be present in the testbed and the workflow that must be followed. For instance, a fingerprinting based location device must include mechanisms for building the map prior to further evaluation.

The 6G technologies that will be enablers for location have also been reviewed, along with the open research questions. A location testbed may support all or some of these technologies, depending on whether an integrated or partial evaluation of these aspects is required.

Finally, location-aware functions in 6G have been reviewed. In this case, location acts as an input to the functions and must be provided by the testbed. It is up to the specific experiment whether the source of location is part of the test (i.e., the location computed solely by 6G techniques or devices that are present in 6G devices) or just part of the ground truth.

V. ARCHITECTURE FOR A 6G LOCATION TESTBED

In this section, an architecture for a testbed for 6G location will be described, fully detailing each part and the considerations for material procurement. The proposed architecture is meant for implementing testbeds where an iterative approach can be applied. The operators of the testbed will devise experiments to test location devices, location algorithms, or location based functionalities and services (which will be referred to as Device Under Test or DUT hereafter), and program the testbed to perform them and collect data. This data will then be automatically analyzed with previously programmed data analytics mechanisms within the infrastructure of the testbed. The output will inform the operators about the behavior of the DUT and its compliance of certain requirements, and adjustments can be done on it for the next iteration. Once a certain level of maturity of the DUT is reached, it can leave the testbed and further advance in the R&D workflow.

Figure 6 shows the overall proposed architecture. This architecture has four scopes: the physical scope which composes the physical setting of the testbed; the 6G network scope made up of an Open RAN based infrastructure; the service scope containing the applications; and the Research and Development (R&D) scope which adds the testbed functionality to the standard equipment and services of the other scopes. In the following subsections, each of these scopes will be studied in further detail, listing some COTS components that may be procured for implementing this architecture.

A. PHYSICAL SCOPE

The physical scope comprehends all the elements that compose the physical setting of the testbed. Compared with testbeds for other purposes, the physical scope of a location testbed is especially important and complex, since location is a highly environment-dependent functionality. The physical scope contains the physical space, the elements to calculate the ground truth, and the hardware (6G and other technologies such as UWB and WiFi-FTM).

1) PHYSICAL SPACE

The physical space or setting is the environment where the testbed is deployed. It will greatly determine the challenges for location as well as the location solutions that can be used. There are several aspects that must be taken into account for choosing a location:

- Indoors vs outdoors: in indoor scenarios [232], walls and furniture will act as obstacles, making propagation more difficult and creating more NLOS propagation situations. On the other hand, indoor scenarios are also more prone to have more dense deployments, which helps location by having more reference points. In outdoor environments, LOS propagation is more common, and deployments tend to be more sparse. In outdoor scenarios, GNSS systems can also be used for complementing 6G location.
- Mobility of targets: targets that are moving fast or change course will pose several challenges, such as needing a high frequency and low latency in location; and a high Doppler effect [233]. They will also pose challenges to logistics, requiring the physical setup to be especially planned for the mobile targets with the appropriate clearance or elements such as rails or robots [48], [49].
- Density of clutter: in indoor scenarios, the density of obstacles such as furniture, metallic structures, walls, or even people, will define the propagation characteristics and hence the properties of location. In outdoor spaces, the density of obstacles also plays an important role, for instance in urban canyons or parking lots.
- Deployment density: the density of reference points plays a major role in the accuracy of location. Higher densities will normally produce a higher accuracy, at a higher hardware cost. Network access points usually act as location reference points, but to achieve a higher density, location-specific equipment can also be used, even with different technologies [105].
- Special scenarios: the testbed can emulate a generic environment (e.g., generic outdoors or indoors), or specific settings, such as factories [50] for industrial communications and location, cities (on full or reduced scale) for vehicular location [234], etc. Specific location-aware applications will be analyzed in the service scope, but having a realistic physical setting will help to better understand the interworking of the service with the environment.

The physical setting is one of the main decisions to take when deploying a testbed. Since the physical setting is the base over which the rest of the elements will be mounted, it is also important to choose it early in the process of design. Apart from the type of environment, other practical decisions must be taken, such as the total area that the setting will cover, whether it is a public space or reserved only for experimentation, and the layout of the space. The setting can even be nomadic if the purpose of the testbed is to evaluate location in different settings. In this case, a protocol must be put in place to evaluate the terrain, acquire a map and deploy the equipment each time that the setting is changed.

Finally, another aspect that must be taken into account is the spectrum licensing. To radiate in certain frequencies, a license (which can be shared with mobile network operators) and detailed frequency planning is required. Occasionally this is not enough, and to avoid interference with the public mobile network some limits must be respected, such as transmission power, tilt, or distance from base stations of the operator.

2) GROUND TRUTH

The ground truth refers to the actual value of a magnitude, free of estimation error. It is used to validate methods for approximating the value of the magnitude, and is normally taken in measurement campaigns oriented to validation. In the case of location, ground truth is the actual location of a target over the 2D or 3D map of the physical setting. If time is also taken into account (i.e., in the case of moving targets), the ground truth is a 3 or 4 dimensional vector, with a timestamp being one of the components of the vector. It is important to have an accurate ground truth, because the whole purpose of the testbed is to compare the outcome of location algorithms or location-aware mechanisms with the information provided by the ground truth. In other words, the accuracy of the ground truth will determine the validity of the testbed.

The ground truth can be estimated through three possible strategies:

- Markings on the floor: painting marks on predetermined places will ensure that the target is in a known position. The achievable accuracy is very high in this case, with instruments such as laser distance scanners. Another

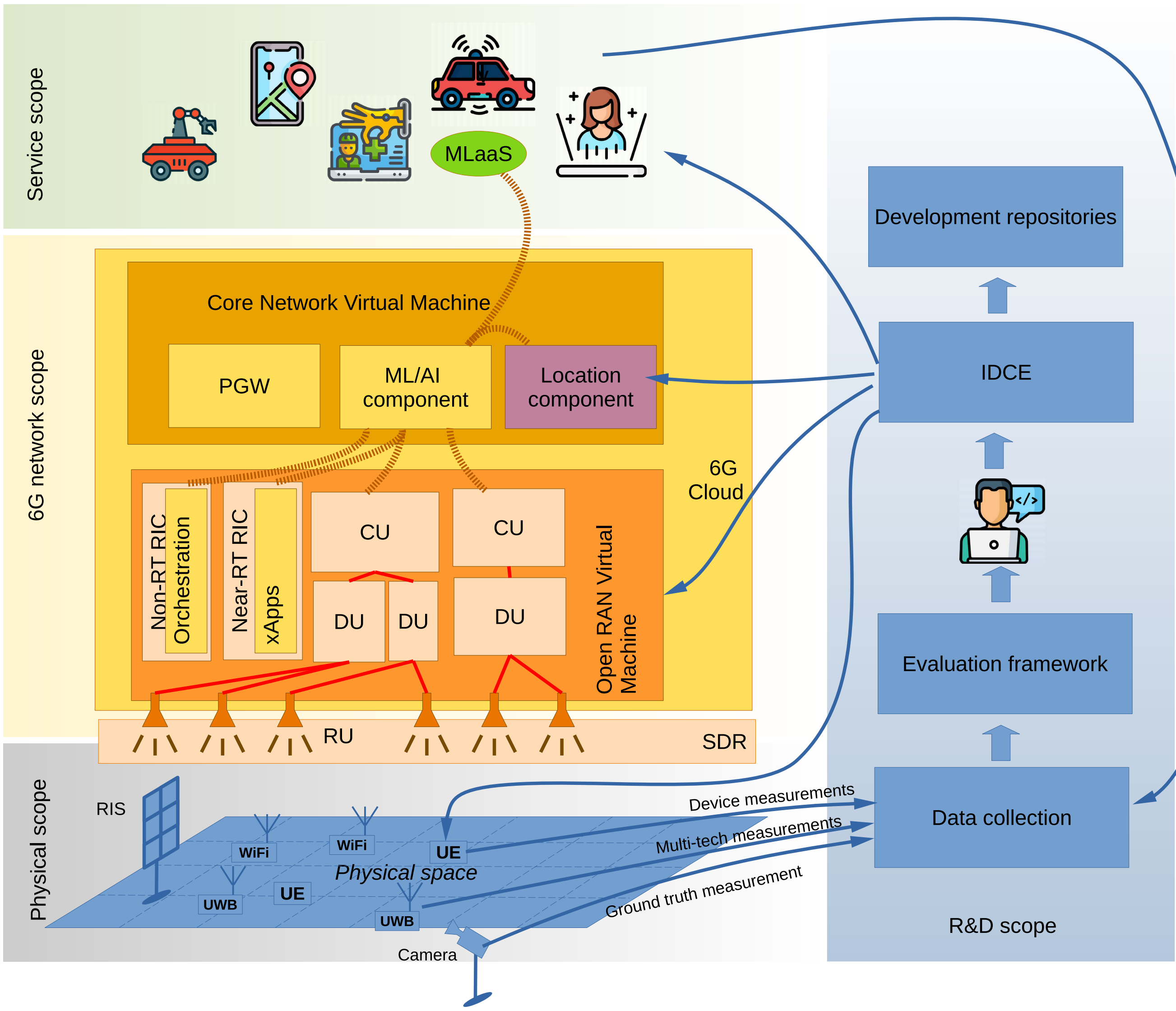

FIGURE 6. **Proposed architecture for the 6G location testbed. Blue arrows indicate the data flow (measurements towards the R&D scope and commands from the IDCE element).**

option is using a grid with fixed size cells, which will help to place targets in known positions. The grid can be used either as a guide for fine tuning the target position (by measuring the distance to the closest grid lines), or as a coarse approximation to the ground truth (by using the position of the cell where the target is located as an approximation for its position). Some examples of testbeds using this approach are [43], [51]. Markings on the floor can provide a very reliable and accurate (down to the mm) 2D ground truth, but it has several problems. Firstly, this approach is not ideal for 3D positioning, since it requires supporting elements (e.g. metallic stands) that may introduce biases in the location methods studied in the testbed (e.g. due to reflections). Secondly, they are not valid for moving objects, since targets must be previously placed on the markings. Thirdly, this approach is not automatable, since it requires to manually place objects on the markings.

- Sensors: location of the targets can also be acquired by external sensors, such as cameras [235], motion sensing devices, radars, or IMUs. These sensors must be strategically placed on the physical setting in order to obtain timely and accurate information. The accuracy that can be achieved depends greatly on the specific device used. In [235], for instance, an accuracy below 10cm is achieved indoors with video feeds. Some sensors can also do 3D location without the need for supports. Sensors also have the advantages of being able to easily measure moving targets and being fully automatable. This comes at a higher cost in equipment, which may also increase the work in redeployments in nomadic testbeds. Testbeds like the one described in [49] use this approach combined with mobile robots.

- Location technologies: if the testbed is not intended for measuring multi-technology location, other technologies, such as UWB, WiFi-FTM, or GNSS can be used for obtaining a ground truth. The accuracy achievable with these technologies varies greatly on the specific device, the radioelectric features of the physical setting, and the density of deployment of reference points. UWB and WiFi can achieve accuracy down to several cm [47], while GNSS varies between several meters [201] down to sub-cm with GPS-RTK [203]. The cost of such technologies is normally higher for more accurate and high-quality equipment, and they also have installation costs (in terms of planning, testing, and validating their setup). All of these technologies support 3D location, moving targets, and are highly automatable. For example, the testbed described in [45] uses this approach.

The ground truth system must be deployed and calibrated before the operation of the testbed. Calibration consists of a validation of the location provided by the system. To do this, several known positions must be measured on the ground truth system, and the provided location must match the known position. Once this is done, the information provided by the ground truth system is considered to be correct. To maintain this trust in the system, regular calibration might be needed. For this, tools like laser distance scanners might be used. The *markings on the floor* approach can also be used for calibration, and a permanent grid can be set up to make this task easier; especially in the case of fixed testbeds. For nomadic testbeds, a calibration phase must be included in the redeployment protocol.

Once set up and calibrated the ground truth system will provide the 2, 3, or 4 dimensional vectors of the location of the targets over the physical setting. An interface between the ground truth system and the R&D scope must be set up. For the *markings on the floor* approach, a user interface that allows to manually introduce the measurements must be developed (e.g., the mobile application described in [42]), taking into account User Experience considerations that simplify operation and prevent human error. In the case of sensors and other location technologies, they will usually provide interfaces for data acquisition, such as HTTP, MQTT, or USB interfaces, so an adapter must be developed to connect it to the testbed data acquisition system.

3) HARDWARE

With the setting and the ground truth in place, the next item to consider for the design of a testbed is the location hardware. This item refers to the hardware of the location system under test, not the ground truth hardware. The required hardware can be classified in the following items:

- Access points and radio elements: the infrastructure of the physical layer of the network must be planned, acquired, and deployed according to a prior design. This will include mainly the Radio Unit (RU), made up of SDR devices (such as LimeSDR [236] or USRP [237]) with diverse types of antennas (dipoles, directional antennas, and mMIMO arrays). Depending on the objective of the testbed, the setup might reflect a well planned network, with a good coverage over the physical setting, or a deployment with coverage holes (e.g., for emulating disaster scenarios or underserved areas).
- RIS: since in 6G RIS will likely play an important role, they can also be part of the testbed. RIS may be deployed on preselected surfaces of the physical setting, with the possibility of moving them around if the purpose of a test is to assess the placement of RIS over different surfaces.
- Terminals: the terminals will be the targets for location. While 6G terminals are still years from being commercially available, the testbed can be prepared for eventually admitting them when they are released. While at the time of writing this paper 6G devices are still far from reaching the market (with few experimental devices starting development [238]), several decisions may future-proof the testbed. One option is to not use COTS devices, but experimental prototypes based on SDR (such as LimeSDR [236] or USRP [237] devices) and programmable platforms, such as PC/laptops, RaspberryPi [239] or HiFive [240]. This will require a deep knowledge of the end service by the testbed operators; or outsourcing the production of such devices to external organizations. Another option is to use 5G devices, especially while a 6G standard is not available and the testbed implements a 5G RAN/Core. Such devices would become obsolete once a 6G RAN/Core is available, but in the mean time, they can be used to reliably perform scaled-down experiments without the need of fully developing experimental prototypes of the end services. They will also provide a better grasp of secondary effects that may not be modeled in experimental prototypes. Such terminals can be static or mobile (carried by vehicles, robots, or persons).
- Computing hardware: With Open RAN, most of the 6G network is completely virtualized, so computing power is a very important requirement. A major advantage of network virtualization is that COTS computing equipment can be used, greatly simplifying the process of hardware acquisition. Therefore, the computing hardware can be standard computers, based on Intel/AMD or ARM [241] architectures. In the near future, the RISC-V [242], [243] architecture is also expected to gain popularity in open systems such as Open RAN. The computing hardware can be either concentrated in one powerful computer, or distributed on a network-connected cloud. Also, hardware for backups (e.g., Network Attached Storage systems) must be acquired, as well as systems for ensuring continuous operations (i.e., UPS or generators, depending on the size of the installation).
- Backbone network: in the case that the computing hardware is designed as a cloud, a backbone network must also be deployed. To ensure low latencies and high bandwidths, it may be necessary to use

optic fiber connections instead of traditional ethernet cables.
- Complementary location technologies: in the case that the testbed includes multi-technology location, other technologies such as UWB and WiFi-FTM may be planned, deployed, and used over the physical setting, and connected to the 6G core network to provide measurements. This design must also reflect the intended objective of the testbed (e.g., using sparse deployments of UWB/WiFi to complement 6G location). This setup will most likely differ from the setup of these technologies as ground truth. In any case, they cannot play simultaneously a dual role as part of the location system under test and as ground truth.

Once all these elements have been planned according to a specific testbed design, they can be acquired and installed in the physical setting. Installation may be permanent or removable, and in the case of nomadic setups, impact over the environment (e.g., holes in walls for mounts) must be minimized.

Another important aspect to take into account are replacements. Ideally, replacements must be available before needed, so acquisitions should be done with a margin for extra replacement parts. Replacements for commercial equipment (such as specific models of smartphones) can be especially hard to find in the market after some time.

B. 6G NETWORK SCOPE

This completely software scope contains the 6G RAN and Core network. To run the network, either cloud or local computing infrastructure is needed (which are part of the physical scope). To successfully run a testbed, such a network implementation must be open source, or at least, fully configurable with the possibility of adding new custom functions. The 6G network will also contain all the required logic for Edge Computing and MLaaS. The 6G network will run two types of virtual machines: the Open RAN virtual machine, and the core network virtual machine; each made up of several software entities.

1) OPEN RAN VIRTUAL MACHINE

In traditional networks, the RAN is a separate entity made up of a network of physical nodes containing different network functions. In the Open RAN approach, that started with 5G and will be fully adopted in 6G, all the functions are virtualized and run as microservices in containers such as Docker or KVM. As described in Section IV-B, to have a functional 6G network, the following virtual elements would be needed:

- Base stations: what in prior generations is a single entity, in Open RAN can be made up of three disaggregated elements: the RU (which stands between the 6G network and the physical scopes), the DU (which controls several RUs) and the CU (which controls several DUs and may run edge services). The RUs were described in Section V-A. The DU and CU will be software components running as microservices in the physical computer that is the closest to the RUs, and can in some cases be integrated as a single element.
- Near-RT-RIC: should be deployed in a physical machine where it has ample resources and priority, as well as a good connectivity with the CUs of the network. This virtual function should also support the easy addition of microservices through a remote connection such as SSH or a remote package manager, to easily add and remove xApps.
- Non-RT-RIC: the network management functions running in the RAN (e.g. decentralized optimization algorithms) will be done in this element, which will run either in the computing infrastructure of the testbed or even in a remote cloud.

Implementations for 6G Open RAN do not exist yet, so two options can be weighted: either using a 5G Open RAN as a placeholder for 6G, or using an experimental 6G Open RAN platform. The first option can be used for developing services and schemes with performances that are scaled down to the capabilities of 5G, with the promise of providing better results once 6G functions are available to them. This option must be done with a path for upgrading the RAN to 6G once a viable implementation exists. Experimental 6G Open RAN platforms will be developed on the basis of 5G Open RAN [22], so most likely, they will be able to work out of the box, albeit with more effort from the operator of the testbed and subject to possible software instability.

In any of the two options, the adoption of open source solutions, such as the O-RAN Alliance [169] implementation, will have several advantages: access to source code allowing to better understand the inner workings of the system and to modify any functionality, easy development of new functionality that depends on the CU and DU microservices, and most importantly, future-proofing the testbed by ensuring that it will support a 6G (and beyond) Open RAN once it is available.

2) CORE NETWORK VIRTUAL MACHINE

The core network of a mobile network traditionally contains the higher layer functionality of the control plane, as well as the Packet Gateway (PGW or the equivalent function) which connects the user plane to the Internet. 2G and 3G also had gateways to the Public Switched Telephone Network (PTSN), but in 4G an onwards this element was removed in favor of Voice over IP (VoIP). In 5G the User Plane Function (UPF [244]) acts as an evolved PGW, with additional QoS functions, packet inspection services, and multi-RAN support. In the control plane, the 5G core network contains functions such as the Access and Mobility Management Function (AMF) and the Session Management Function (SMF). These functions are already virtualized in 5G. In 6G, it is expected that these functions are complemented with novel services such as the MLaaS component and a specific component for user location.

The AI/ML component [17] will offer ML to other core network functions, RAN functions that are not delay-sensitive (e.g., those running on the Non-RT-RIC) and even end services through a yet to be established MLaaS API. The AI/ML functions will be a virtual machine running over a physical machine with specialized ML accelerators (such as CUDA-capable GPUs [245] or the Intel Movidius [246] platform). Therefore, to have a powerful AI/ML component in the testbed, the acquisition of such devices would be recommendable, and the development of a standardized interface to the rest of the core network, RAN, and end services.

The user location component will be of utmost importance in the proposed testbed architecture. It will contain the functions that gather information from the RAN, such as measurements of RTT or RSRP in 6G, measurements from other interconnected systems such as UWB or WiFi-FTM, and measurements from the terminals (e.g., GNSS readings), to estimate a user location. This component may offer the real-time calculated location to the terminals, other network functions or external services (if the user privacy settings allow this), and also perform location-aware computations, such as tracking and mapping. There are ongoing works for implementing this component for 5G networks, such as the LOCUS project [31]. In the 6G testbed, this component may be populated with the functionality that is standardized in the next 3GPP releases leading to 6G; but at the moment of writing this paper, it will be an empty component which development will be the very objective of the testbed. Therefore, it will be the main component that is connected to the R&D scope; where new schemes will be developed, deployed in the location function, and validated.

Just as in the case of the 6G RAN, there is no standard implementation for a 6G core network yet. Again, the testbed designer can opt either to adopt an existing 5G Core network (such as [247], [248] and [249]), or using an experimental 6G core network, with the same implications as in the Open RAN part. Also in this case, it is recommendable to use an open source implementation that adopts new technologies leading to 6G.

C. SERVICE SCOPE

The end services will use the 6G network for implementing different location aware applications over the physical setting. These services will be fully controlled by the testbed operator, such that they can be programmed, monitored, and assessed. It will run over hardware such as smartphones, laptops, mobile robots, or drones, on the terminal side; and cloud servers on the backend side. In the case of a location testbed, location-related services will be evaluated. Such services either depend on location (i.e., are location-aware) or impact the network in different manners depending on their location.

Location-aware services are those that need to know the location of the users with requirements such as accuracy, latency, or frequency. A comprehensive list of such applications is given in Section III. The testbed must measure two aspects:

- Application performance: given a specific set of location characteristics, the testbed will measure the performance of the applications by closely monitoring them with sensors embedded within the DUTs or with external sensors (such as cameras). These monitoring systems will measure different SKPIs such as navigation errors in robots or self-driving cars, or QoPE in XR applications.
- Location as a Service performance: once the requirements of specific services are known, the performance of the location component will be monitored for different services, finding whether it fulfills the requirements, the factors that may affect the QoS, etc.

The selection of applications will determine the purpose of the testbed. General purpose testbeds may add generic services, such as location with potentially mobile users. Special purpose testbeds may, on the other hand, acquire a set of services that are specific to a special scenario. These choices will be complemented with specific choices in the physical layout, emulating the environment where these services will run. Ideally, such applications must also have open specifications, such that developing components to connect them to the R&D scope for monitoring and for programming is feasible.

Applications will also play a role on creating different effects that may affect the location function. For instance, functions that rely on the aggregated location of users (such as location-aware network management algorithms) will ultimately depend on certain services running within the coverage area of the network. This scope will have to be able to emulate different situations where the services are not location dependent, but where their characteristics will affect other location dependent functions. For this, full applications or simply traffic emulators can be programmed and deployed in the testbed; the only requirement being that they can be controlled to perform experiments.

D. R&D SCOPE

This scope comprehends all the actual monitoring of the other scopes and development work. It comprehends a data management system that will receive ground truth measurements, measurements from devices and from the network, from external systems, and from end services. These measurements will be stored in data repositories and processed in an evaluation framework, offering the developer insights on the DUT. The developer will then use the obtained insights to modify the DUT with an Integrated Development and Control Environment (IDCE). From the IDCE, new programs or configurations can be deployed to the physical, network, and application scopes; the full testbed can be controlled and progress of the development process can be saved in development repositories where the work may find a path to market.

1) DATA MANAGEMENT SYSTEM

The data management system is one of the most complex parts of the testbed. While the other parts of the system may be implemented potentially with COTS equipment, the data management system must be developed customized for the acquired materials. The data will come from 7 different origins:

- The 6G RAN: magnitudes present in the network operation, such as raw measurements used for location (e.g., RTT, RSRP, etc.), KPIs of the different RAN components (such as total RU Throughput, packet loss, etc.) or computing load of the virtual machines, etc.
- The location component: as one of the most important components of the location testbed, the location component will be heavily monitored, measuring magnitudes related to the estimated location, such as the accuracy, the compliance of requirements, the resource consumption, etc.
- The 6G core network virtual machine: other components of the 6G core network may also be of interest for the development of location-aware management, such as the throughput at the UPF, or the resource consumption in AI/ML services.
- Device measurements: raw measurements taken from the device for location estimation (RTT, RSRP, etc. from the 6G network or other RAN technologies), GNSS measurements, device status, etc.
- Multi-tech measurements: range measurements from complementary technologies such as UWB or WiFi-FTM.
- Ground truth measurements: actual positions of the location targets, taken with the devices described in Section V-A. As earlier stated, for the R&D scope, these measurements will be considered free of errors.
- Service measurements: as described in Section V-C, numerous performance measurements must be taken from the service scope. Such measurements will be highly dependent on the specific service.

All of these data sources must be collected and centralized in the data management system, where some normalization must take place before the data can be stored and used. To do this, the data management system is made up of several subcomponents (Figure 7):

- Data collection network: one or several networks will be set up to connect the devices where the data is collected for the testbed. Such networks will ideally be isolated from the RANs of the technologies that are being tested. Depending on the device, alternative network interfaces will be used for this purpose. For instance, for DWM1001 UWB devices, USB, and BLE connections [250] can be used to transmit the UWB measurements. In USRP SDR devices, Ethernet and/or PCIE interfaces can be used; and in smartphones, USB-OTG, or BLE can be used, freeing 5/6G, WiFi, and UWB for the tests. This implies that the data collection network will be on its own a multi-technology network, requiring that the data management system has the corresponding interfaces.
- Data collection probes: specific components developed for the device over which each of the data sources is located that will collect the required data and send it to the testbed through the data collection network. The data that will be collected will come from sources that have varied data collection interfaces, so custom components using the tools provided by the manufacturers must be developed for each source, with different challenges in each one. For instance, collecting data from proprietary devices in the service scope may be very difficult due to lack of developer documentation or access to certain functions. Another challenge is the maintenance of a large code base with components of many different platforms and programming languages (e.g., C-based probes for USRP SDR [237] devices, Kotlin code for Android smartphones, etc.).
- Probe drivers: the probes, that will be running in the devices must be managed remotely by the testbed. The driver for each probe will connect to the probe over the data collection network and send start/stop commands, reconfigurations, software updates, etc. Since each probe will have a different behavior (i.e., different protocols, command formats, etc. depending on the specific platform they are programmed for), these drivers must provide a common interface towards the testbeds with a common set of commands and parameters, to simplify the orchestration of the testbed.
- Data format adapters: the probes will extract data in formats that highly depend on the platform and the specific magnitude that is being measured. For instance, RTT measured in Google WiFi devices [251] will come as a Kotlin or Java object, while RTT measured in DWM1001 comes in plain text. The probes should not do any conversion to minimize the impact on computing resources and battery on the monitored devices, so they will capture this raw data and send it to the testbed, where the adapters will translate them to a common format.
- Data storage: the data obtained will be stored in a database that can later be accessed by the evaluation framework. The database must fulfill two requirements: a high capacity and a relatively high throughput. Since the testbed is designed to assess the performance of location, and not to control any system in a closed loop, latency is not a major issue.
- API interface: once the data is stored, it must be accessed from the evaluation framework. Here, an open and well documented interface must be used. Most databases already offer this, but in some cases the interface may be cumbersome and security policies within the organization running the testbed may limit the network access only to HTTP/HTTPS requests. In these cases, Representational State Transfer (REST) interfaces may be a good option to add to the data management system and act as the external query interface. Technologies such as Django REST Framework [252] may simplify the development of this interface.

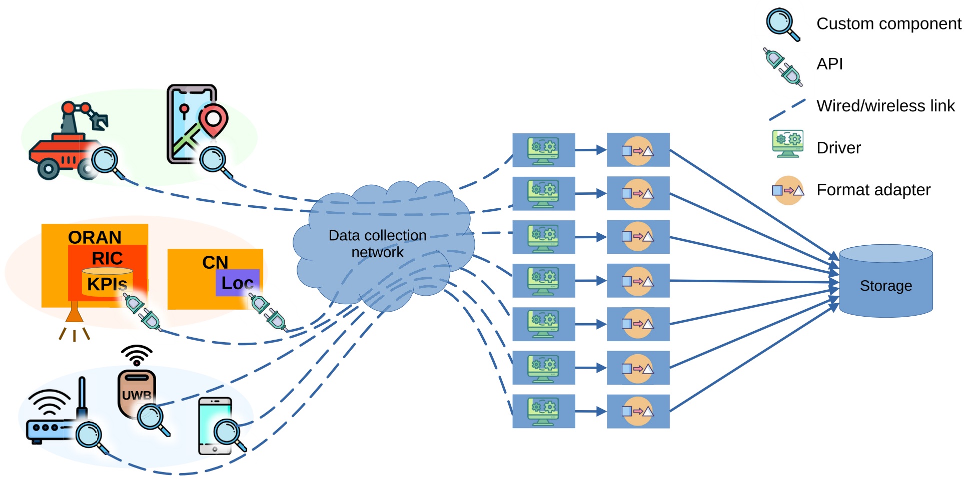

FIGURE 7. Parts of the data management system. Data is acquired with APIs where available and with custom components elsewhere.

2) EVALUATION FRAMEWORK

The evaluation framework will take the measurements collected in the data repositories and extract the derived metrics which assessment is the objective of the testbed. The evaluation framework produces human-readable outputs that will help developers iteratively work on new location schemes and location-aware applications.

The evaluation framework will extract the magnitudes (accuracy, latency, and frequency), and assess whether they reach the minimal requirements of the applications (as described in Sections III and IV-C). These metrics will be extracted from the data collected from the data sources described in Section V-D1.

The extraction of these metrics may imply a large amount of computations, with relatively low complexities (mainly distances between the ground truth and the estimated position, differences of the performance indicators with the requirements, etc.). The key point in this component is flexibility (in other words, the ability of setting up new calculations for different tests) and rich statistical analysis functions. Platforms such as Python [253] and Python-based data analytics tools (such as Jupyter [254] or Orange [255]), R [256], SPSS [257] or Matlab [258] may all provide such tools. It is up to the developer preference to choose among these platforms, as well as the cost of licensing.

Another important task that this block will do is live representation of metrics for live demos. For this, the aforementioned platforms offer tools for live graphics, and platforms like Grafana [259] can be deployed too.

Finally, libraries such as FPDF [260] can be used in this component for automated reports for product evaluation and certification.

3) INTEGRATED DEVELOPMENT AND CONTROL ENVIRONMENT

This element is the interface of the testbed users (developers and researchers) with the rest of the system. It allows full control of all the elements and enables the R&D workflow. This workflow, as described earlier consists of two roles: testbed control and location development.

The control work that must be done on the testbed consists of four steps:

- Designing an experiment: the first phase will be to determine the objective of the experiment (i.e., what needs to be measured) and the DUT. It may be the performance of a location method, a location device, or a location-aware service. Along with the objective and the DUT, a hypothesis must be formulated, defining the expected results; as well as the boundary conditions and the environment setup.
- Configuring the environment: the next step is to configure the environmental variables to the experimental setting design specifications. This may involve reconfiguring the elements of the physical space, changing network parameters and service configurations. The evaluation framework must also be programmed to collect and show the designed output magnitudes.
- Launching the experiment: the experiment will be run in an automated or manual manner. This stage may involve moving elements through the physical space to assess for mobility in the DUT.
- Collecting results: the testbed will automatically collect measurements, store them, and process them in the evaluation framework. This stage consists of extracting information from the results of the evaluation framework, comparing them with the hypothesis and formulating conclusions based on this information.

The results of the experiments may lead to additional development on the DUT. To do this, the IDCE will offer functionality to help in the development, such as text editors with syntax highlighting and support for all the possible programming languages that the DUT may use. The IDCE will allow the users to easily push updates to the DUT, whether it is an end service running in the cloud and/or terminals, a 6G orchestration function running in the Non-RT-RIC, an xApp running in the Near-RT-RIC, or a location algorithm running in the location component of the 6G core network. The IDCE will also offer these facilities for development of computation programs in the Evaluation framework and for updating software components throughout the testbed.

Some testbeds that use a similar approach are [49], [50], [53], [232]. Another function that the IDCE must offer is some degree of automation for live demonstrations, where it may replay experiments with minimal operator intervention.

The IDCE will run in one or several computers. The main terminal may be a laptop or desktop computer, with the appropriate network connections. Secondary terminals may be used for assistance during the execution of experiments, for instant, tablets, or smartphones that allow control of certain components of the testbed (as done in [42]). For this role, consumer-grade devices with average computing power can be used, reducing material costs, since heavy computation is not done on them.

Regarding the software of the IDCE, it must have several interfaces:

- With the 6G network: it must be able to modify the network settings to adjust the required experimental conditions, and start/stop functions.
- With the end services: to configure them and send different events, such as connectivity interruption, user interaction, etc. This interface is dual, with one side being on the user terminal, and the other in the remote server.
- With the physical scope: to control the environment before and during the experiment. Some of the interactions must be done manually (e.g., moving partitions), while others can be automated with elements like robots as done in [48] and [49].
- With the development repositories: to publish development work on the DUT.

For the implementation of this component, two approaches can be used. The first one is to use discrete software components, some of them provided by vendors (e.g., software for the control of the 6G network, Integrated Development Environments, such as Spyder [261] or Matlab [258]) and others customized for the testbed (e.g., control logic for the probes). While this option may result in a less integrated environment, it may also be less costly. The other approach is to develop a fully integrated environment, where all the functions are integrated into a single interface. This option may be more expensive, but give place to a much more streamlined workflow.

4) DEVELOPMENT REPOSITORIES

The testbed will ultimately be used for developing new location schemes or location-aware functions. During the R&D workflow, it is expected that the maturity of the DUT improves iteratively, resulting in a code that can be distributed either within the entity that owns the testbed, or publicly. In parallel, the development process may be done by a team of developers, so a control version system would be required to have a seamless workflow. For all these reasons, a repository with version control would be a very important component of the R&D scope. Platforms such as GIT [262] can be used for implementing this element.

E. KEY TAKEOUTS

This section described an architecture for implementing a testbed for 6G location. The architecture has four loosely connected scopes, which enables updating each of them separately and therefore greatly simplifies extensibility as 6G technologies progress.

The Physical scope concerns all aspects that are related with the environment of the network and services, such as the physical space, the measurement of ground truth, and the hardware.

The 6G network scope contains a full 6G network, which must follow the latest developments and standards. Thanks to technologies such as Open RAN and SDR, this can be done with ease and relative cost-efficiency.

The service scope includes all the end services that rely on network-based location, and can be used for end-to-end evaluation.

Finally, the R&D scope includes all the control logic for the testbed, including data acquisition and processing, a development environment, and data and code repositories for integration with external systems.

For each of these scopes, a small overview of existing technologies is done, showing the path to begin a real-world implementation.

VI. IMPLEMENTATION EXAMPLE

In this section, an example of an implementation of the proposed architecture is described. The purpose of this section is to show how the guidelines disclosed in this paper can be applied in practice, and how they can be used to perform a successful test. Specifically, a nomadic testbed was implemented in the University of Málaga (UMA) in the context of the LOCUS project [31] to measure the performance improvements achieved with range fusion [105] over single-technology location. In this case, the range fusion algorithm is the DUT.

The experiments that were carried out seek to obtain the reliability and accuracy of the location service in two different scenarios: a classroom for the education use case [47] and a building under construction [263]. The hypotheses of these measurements are twofold. On the one hand, it is expected that network location will help improve the coverage of the accurate location systems (WiFi-FTM and UWB in this case), and therefore, its reliability. On the other hand, it is expected that, in points where there are more than one accurate technology available, it can help improve the accuracy. The experiments will show whether these hypotheses hold up or not.

A. PHYSICAL SCOPE SETUP

Two physical settings have been selected for the experiments:

- Education use case: two laboratories separated by a partition and connected by a stretch of open air corridor in the UMA were selected. Figure 8 shows a map of the

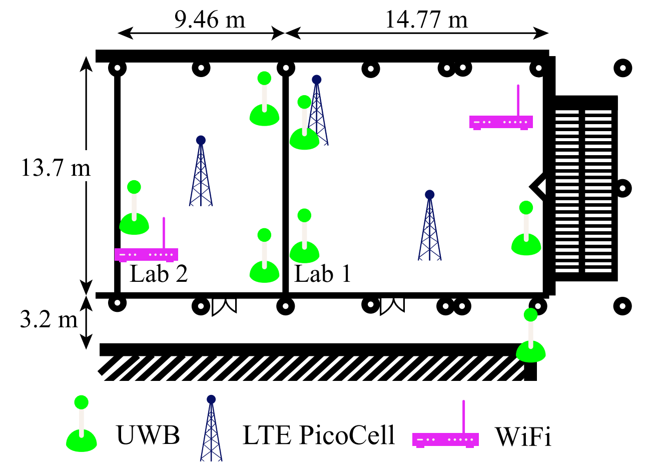

FIGURE 8. Physical layout of a testbed for location for education.

FIGURE 9. Picture of the classroom scenario with ground truth markings on the floor.

FIGURE 10. Construction scenario where the portable testbed was deployed.

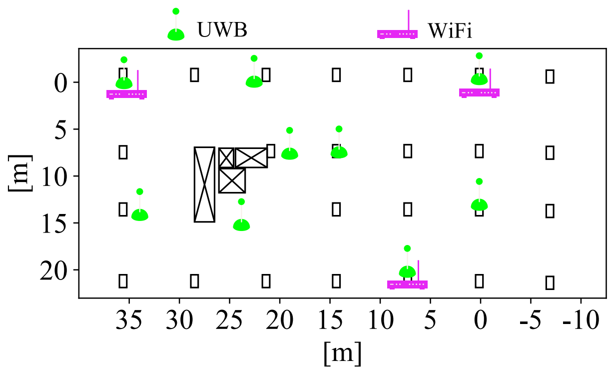

FIGURE 11. Physical layout of a testbed for location in a construction site.

scenario. The location of the reference points of three different technologies (UWB, WiFi FTM and LTE) is also shown. The clutter in this scenario is moderate, as shown in Figure 9, consisting of long workshop tables with PCs, monitors, and electronic lab instrumentation. The total size of the scenario is 24 × 17 meters with a height of 3.5 meters. The ceiling contains some structural elements and light fixtures.

- Building in construction: the selected building (Figure 10) was in the phase where the main structure was already constructed, with external walls and internal partitions still missing. The measurements were taken in three different floors: the ground floor (without walls), and two underground floors, where the parkings were meant to eventually be constructed. In the underground floors, the foundations protected the building from surrounding underground water aquifers. The constructed structure was made up of reinforced concrete, and large metallic structures such as cranes were present. The total area covered by the scenario was 45 × 28 meters. Figure 11 shows a map of the −1 floor, where the WiFi FTM and UWB reference points were installed. It can be seen that there are no partitions in the space, and only the pillars and some walls conforming a stairway (towards center-left of the scenario) are present. The measurement points were replicated in the ground and −2 floors.

In these scenarios the following radio equipment was deployed:

- DWM1001 UWB [250] from Qorvo as high accuracy location technology. Each reference point was powered by a USB adapter.
- Google WiFi routers [264], with WiFi-FTM support.
- Indoor Huawei LTE network [112] as cellular technology (only used in the education scenario).
- Experimental terminal made up of a stock Google Pixel 3 (which supports WiFi-FTM) with two DWM 1001 UWB tags attached through BLE links (Depicted in Figure 12 and summarized in Table 2).

TABLE 2. Summary of the characteristics of the components of the experimental terminal.

Device	Google Pixel 3	DWM 1001
Role	Controller, range sensor, data concentrator, backhaul connectivity	Range sensor
RATs for ranging	LTE, WiFi-FTM	UWB
CPU	Snapdragon 845 (ARMv8)	nRF52832 (ARMv7)
Sensors with potential use for location	Camera, accelerometer, gyroscope, proximity, compass, barometer	Accelerometer

FIGURE 12. Experimental terminal running the data acquisition app.

Regarding ground truth, in the three scenarios the *markings on the floor* approach was used, establishing a relation between the sample and the point using time stamps. Figure 9 highlights the locations of the markings on the floor for the education use case.

B. 6G NETWORK SCOPE PARTIAL IMPLEMENTATION

Since 6G is still not available, and the objective of this testbed is not to test the radio aspects of cellular technologies, WiFi was used as a backbone for connectivity. LTE was used for network-based measurements in the education scenario.

The LOCUS platform [31], [177] devises a network location function as the one described in Section V-B, that receives information from the terminals, network, and contextual sources to determine user location, and also acts as location server. In this testbed, an implementation of the location function was done, following the LOCUS platform definition, as shown in Figure 15 with the following elements:

- Data collector: collects ranging information that may come from the reference points or the terminal. In this specific case, the ranges were measured in the terminal for simplicity.
- Data parser: unifies the format of the collected data and translates LTE power measurements into distance estimations. This is not done for UWB and WiFi-FTM because these technologies directly provide a range estimation.
- Location estimator: using the measured ranges, estimates the location of the user with range fusion as described in [47] and [105].
- RabbitMQ messaging service: connects the three elements and also acts as external interface for location-dependent services and functions. As an experimental platform no intermediary element is used, but in more mature prototypes, an element that also implements authentication and permission flags should be used as public interface.

The location function will run in a laptop that also contains the R&D scope functionality.

The data provided to the location service is collected in the terminal, using an Android app that collects range estimations from the WiFi-FTM API [251], the UWB devices attached to the smartphone [265] and the RSRP of the serving, and neighbor LTE cells [266]. The app sends this data encoded in JSON to the location service. Figure 14 shows a screenshot of the developed application, where the name and coordinates of a ground truth point can be inserted and the acquisition of data commanded. Figure 13 shows the flowchart of the concentrator component that runs once the data collection is commanded in the GUI and that collects the data captured by background processes.

C. SERVICE SCOPE MEASUREMENTS

A generic service scope was implemented in this case, since E2E measurements were not being taken. The only important aspect in these experiments was measuring the following metrics, which will affect the potential end services:

- Reliability: probability that the network can provide a location. It will do so if the terminal is in coverage; that is, if it is within range of 3 reference points (for 2D location). In these experiments, the reliability will be measured as the proportion of measurement points in coverage.
- Accuracy: represents the correctness of the estimated location. In these experiments, the average horizontal (2 dimensional) accuracy will be measured in meters.

D. R&D SCOPE IMPLEMENTATION

The R&D scope will be very simple in this case, including the following elements:

- Probe in the location service: a RabbitMQ consumer will be implemented, listening to the publishers of the three other elements.
- Collection network: since the location service will run in the same laptop as the R&D scope functions, the probe will be connected through the loopback network interface.
- Reliability estimation: the raw data will be explored to find how many reference points are visible in each sample.

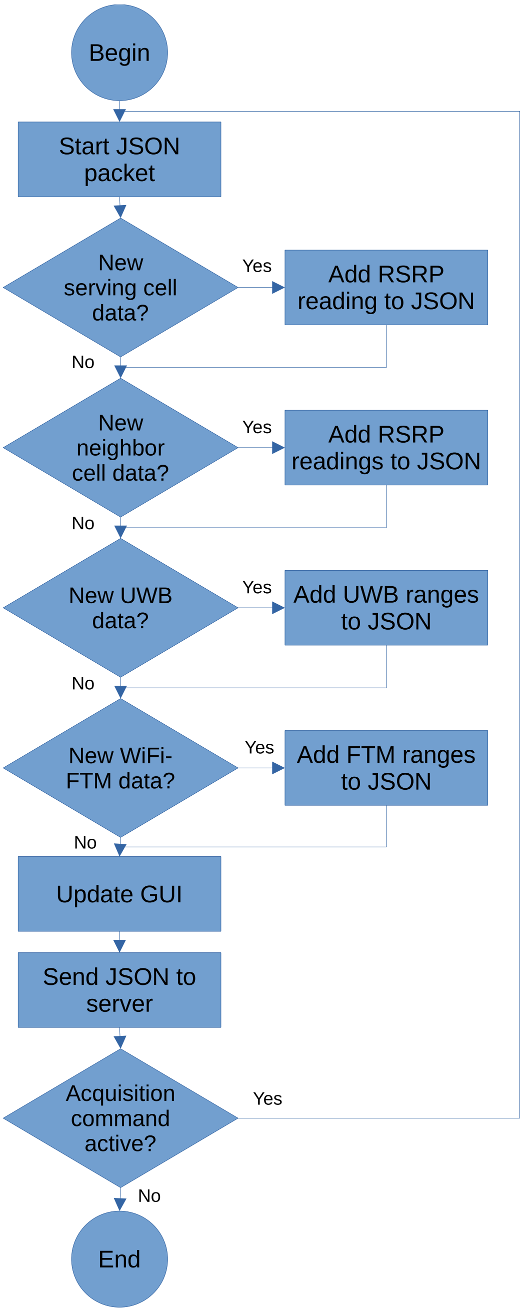

FIGURE 13. **Flowchart of the data concentrator in the Android application.**

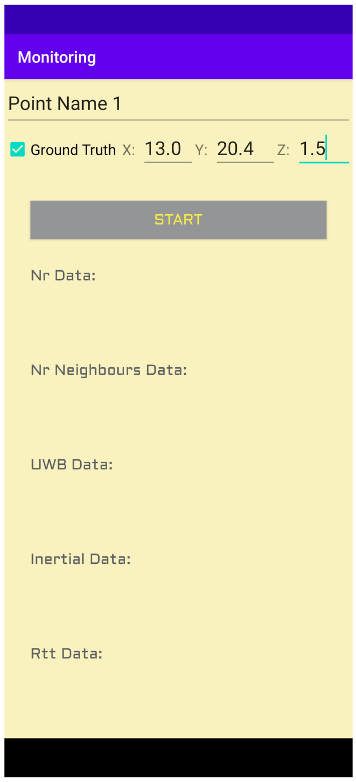

FIGURE 14. **Android app acting as a probe in an experimental terminal.**

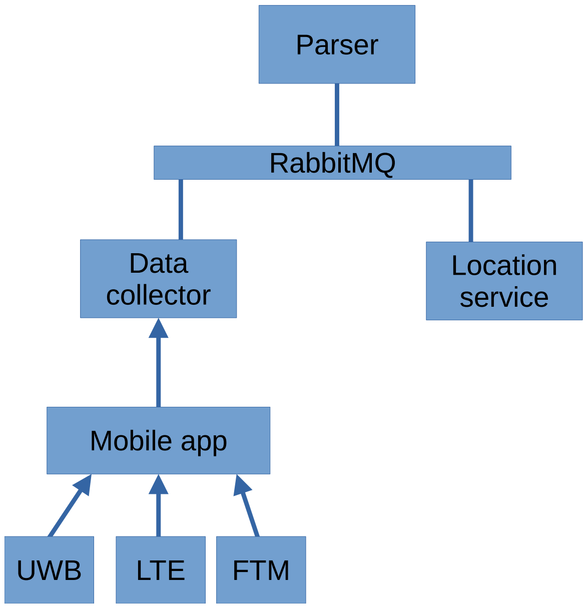

FIGURE 15. **Location functionality block inspired on the Locus [31] platform.**

- Error estimation: the error will be calculated comparing the location service with the ground truth offline. A prior data preparation phase will first associate the time stamps to ground truth locations (based on manually taken annotations), and then add the ground truth location to the collected data based on their timestamps. The error will then be calculated and the Empirical Cumulative Distribution Function (ECDF) represented.

E. RESULTS AND DISCUSSION

The reliability results are represented in Figures 16 and 17 and the accuracy results in Figures 19 and 20 for each scenario using both a single technology and range fusion.

It can be seen that, in all scenarios, reliability is higher when using fusion, since it "fills the gaps" where less than three reference points of a single technology are present. In the education scenario (Figure 16), UWB on its own provides a reliability of 48.46% and WiFi-FTM on its own, 85.77%. The fusion of both improves the reliability to 95.77%, since points that previously were not covered by a

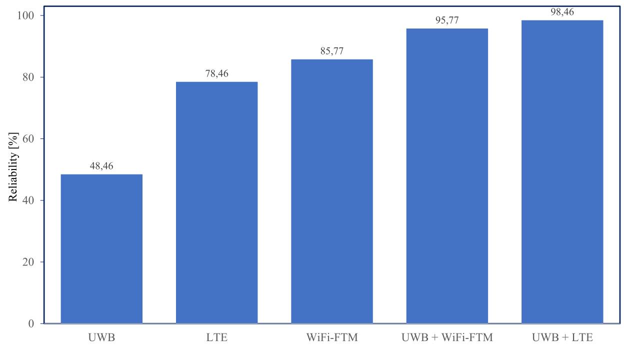

FIGURE 16. Reliability measurement results for the education scenario, showing the proportion of readings that have enough reference points to perform location.

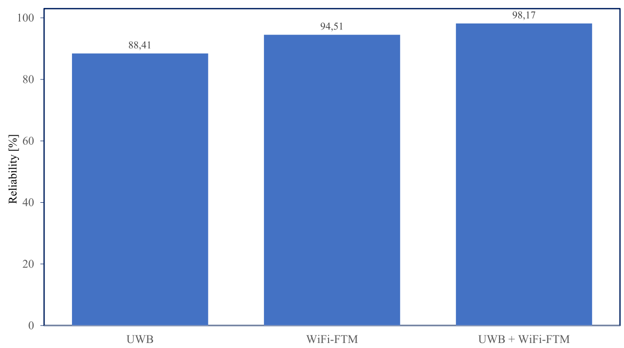

FIGURE 17. Reliability measurement results for the construction scenario, showing the proportion of readings that have enough reference points to perform location.

technology on its own due to insufficient visible reference points can now benefit from using additional reference points. This is also the case with LTE, which on its own provides a reliability of 78.46%, but helps improve reliability of a pure UWB setup up to 98.46%. In the construction scenario (Figure 17), a similar behavior can be observed, with UWB on its own having a reliability of 88.42%, WiFi-FTM 95.51% and the fusion of both 98.17%. In this case, the nomadic testbed did not allow taking LTE measurements, so its effects cannot be evaluated for this scenario.

Figure 18 shows the ground truth of the measurements in the classroom and three different estimations: with UWB only, with WiFi-FTM only, and fusion of both. The improvement of location accuracy with fusion is obvious, and can also be observed in Figures 19 and 20. When more than three highly accurate ranges are used, accuracy will be higher due to the overdetermination of the WLS problem. In the education scenario (Figure 19), UWB has a 90th percentile of error of 5.61 m, WiFi 9.33 m and the fusion of both reduces the error to 1.46 m. On the other hand, if an inaccurate ranging technique is used, then accuracy will be low. This is very obvious in the fusion of UWB and LTE, which increments the 90th percentile of the error to 34.55 m. This highlights that the role of LTE in this case is not improving the accuracy, but the reliability, as shown in Figure 16. The inaccurate locations are replacing what otherwise would be a sample without enough ranges to estimate location with a single technology. In the construction scenario location is generally slightly less precise than in the education scenario, having values of the 90th percentile of the error of 14.6 m for UWB, 7.75 m for WiFi-FTM and 8.23 m for fusion. In this case, overdetermination does not improve the precision of WiFi-FTM. As Figure 20 shows, UWB is much less precise than WiFi-FTM in this scenario, and fusion produces some results that are very close to pure WiFi-FTM. Combining this information with Figure 17, it can be seen that the effect of UWB here is an improvement over the reliability, similar to what LTE did with UWB in the education scenario.

F. KEY TAKEOUTS

This example covered a trivial testbed used for the specific demonstration of a range fusion algorithm in different scenarios. Due to the limited scope of these experiments, only a partial implementation of the architecture was required, but a more sophisticated setup would add flexibility for different kinds of experiments, as well as extensibility during the development and rollout of novel 6G technologies in the future.

VII. CHALLENGES

While the proposed architecture can alleviate many of the difficulties found when implementing and operating a location testbed, there are some important challenges that may be present in some settings. When building a testbed of any type, there are some general administrative challenges that are almost always present, such as the allocation of the required physical space, the procurement of funds, etc. There are other challenges that are specific to 6G, which are reviewed in this section, along with the outline of some possible lines of action. These challenges can be classified in two big groups: administrative (those related with the non-technical factors of the testbed) and technical (those related directly with the technical components).

A. ADMINISTRATIVE CHALLENGES

Administrative challenges cover the difficulties related with the management of financial resources, regulations, and business relations with vendors. These challenges are often very limiting and may impose restrictions on the technical scope, such as the type of experiments that can and cannot be done in the testbed. In the case of 6G, the following challenges may be met:

- Availability of 6G equipment and vendors: 6G is still far from having a standardized implementation [267]. The techniques that will be included are not even decided; all that can be found in the bibliography is still merely speculative. This may make it difficult for designers to choose the exact components that will go into the testbed. Moreover, because there is no 6G hardware/software commercially available yet, it may be difficult to justify the acquisition of highly experimental

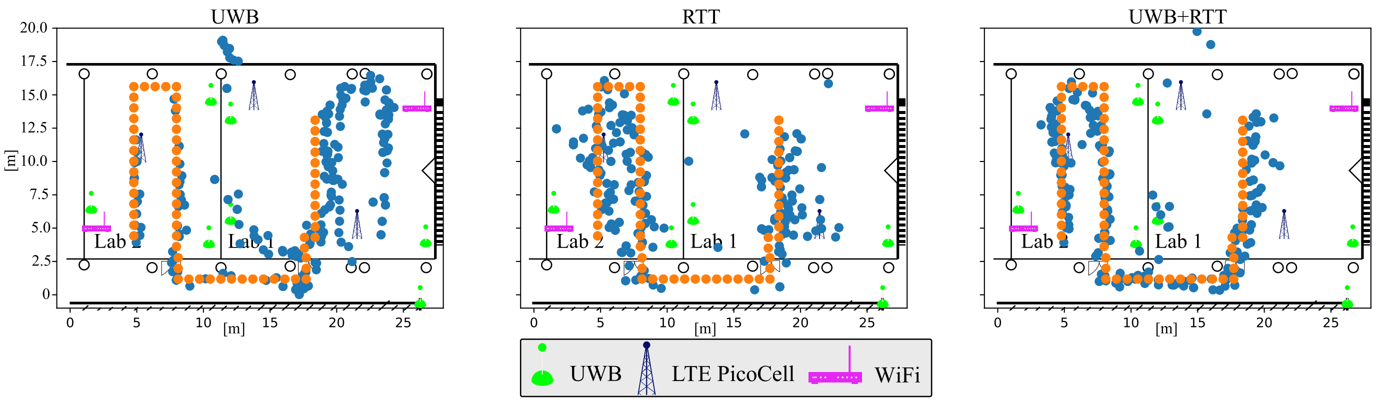

FIGURE 18. Sample of estimated locations (blue dots) compared to the ground truth (orange dots) in the education scenario using only UWB, only WiFi-FTM and the fusion of both.

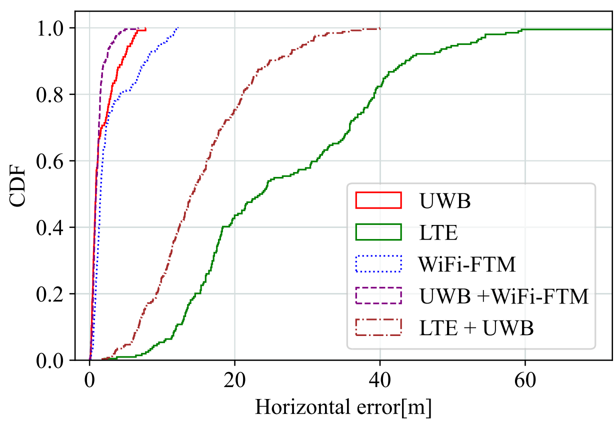

FIGURE 19. ECDF of the error in the location estimation for the education scenario.

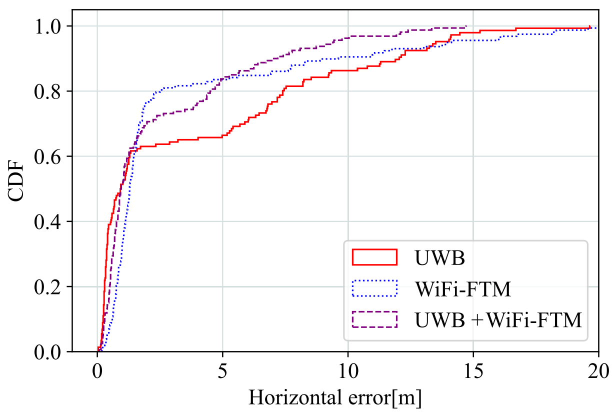

FIGURE 20. ECDF of the error in the location estimation for the construction scenario.

(and often expensive) hardware to accounting sections of the organizations that are implementing the testbed. Once decided and approved, the procurement of components may also be difficult, with a limited set of vendors of specific experimental hardware. From the administrative point of view, there is no clear solution to this challenge, so finding alternatives becomes a technical problem.

- Vendor dependency: the reduced number of specialized vendors may become an administrative problem in several different ways. Firstly, the leverage for negotiating prices is quite limited. Secondly, the dependency on one vendor puts the organization implementing the testbed in a vulnerable position in case the vendor stops giving support or upgrades (e.g., because of contract expirations or even bankrupcy of the vendor). Some factors to take into account when choosing vendors should therefore be their solvency, possible offers of extended support and more importantly, the use of generic components that are well documented and can be supported by third parties in case of need. The use of open source software and hardware components is a good warranty to avoid vendor dependency [268].
- Vendor limitations: some vendors offer their solutions with great limitations, such as the inability of modifying firmware or accessing core components of the system. These limitations may be imposed in several ways: by license or by obfuscation of functions. These terms of service limit the types of experiment that can be done with the components, becoming a technical challenge. From the administrative side, selecting vendors taking into account the lack of limitations should be a priority, but given the reduced number of vendors, it may sometimes be impossible. The establishment of agreements for joint research can then be used for obtaining improved access to the acquired components.
- Spectrum licensing: in the case of a mobile network testbed, one major administrative aspect is obtaining the rights for radiating into licensed bands. Since there is a commercial interest in the usage of such bands, it is often limited to operators that are reluctant to yield part of their capacity to research facilities. Moreover, as 6G is still under development, its bands are still not allocated and they are prone to change once the first digital dividends are released. For organizations implementing the

testbed, especially small ones, obtaining licensed spectrum may be too costly to be feasible. The alternative is to establish partnerships with operators that cede part of the spectrum part of the time such that experiments can be done. Avoiding interference with the wider mobile network may also help to ensure collaboration from operators.
- Privacy: when studying location, it is often overlooked that a terminal is tied to a user. The location of a person is an especially privacy-sensitive data, so there must be mechanisms to avoid collecting or appropriately storing this information following regulations such as the European Unions' General Data Protection Regulation (GDPR) Article 17 [86]. Most testbeds will use their own terminals meant to be used inside the premises of the organization and during work hours. Nevertheless, it is important to implement a clear policy of data protection (e.g., instructing workers not to use the terminals out of periods of time established for experiments). In case that personal equipment must necessarily be used, anonymization mechanisms must be put into place, along with an audit that ensures that personal data cannot be reconstructed.

B. TECHNICAL CHALLENGES

Technical challenges cover the difficulties related with the implementation and operation of the testbed from the purely technological perspective. These challenges stem from the capabilities of the acquired equipment, and are often subject to the decisions taken on the administrative side. The proposal of the architecture described in this paper aims at limiting the effects of such decisions, by making it easier to acquire generic equipment and isolate the limitations of some components on the overall testbed. Still, some challenges may arise when implementing the architecture over real equipment:

- Use of experimental 6G technology: as described earlier, the procurement of equipment may be difficult for experimental 6G components who have been chosen based on speculations. Nevertheless, these speculations are based on educated guesses, and the ballpark estimations that are being made are enough for developing a testbed that can eventually host standard 6G techniques. Thanks to SDN and SDR, generic, COTS hardware can be acquired, which will be compatible with 6G functions in the future. The choice of terminals for end services is another major challenge, since there are no 6G terminals yet, and there are no commercial terminals that can be upgraded to 6G in the future. To future proof the terminals, therefore, adoption of a flexible platform (e.g., SDR devices that can be programmed to act as a specific terminal) will also be necessary. In any case, the cost of acquiring 5G terminals and replacing them with 6G in the future is not economically unfeasible.
- Interoperability of different components: in a testbed, all components should be able to interoperate, that is, they should have the interfaces for the R&D scope to monitor and manage them. This may mean that some development work is required for the adapters (as described in Sections V-D1 and V-D3) which may imply some hacking [269] if the original equipment does not support all the required functions. Vendors may support by either developing the required functions or providing documentation; but using open source components may avoid the need of relying on the vendor. Another problem that may occur is vendor lock-in (i.e., the component is only compatible with other components by the same vendor), which can be avoided again by using mostly open source components.
- Maintenance over time: the proposed architecture is meant to evolve over time, with new components or upgrades to those that are already integrated. This implies that a continuous effort must be done to maintain compatibility between the different components and avoid bad development practices such as the *lava flow* anti-pattern [270], where a software component is quickly modified by different developers to support specific experiments; which may on its turn result in *code duplication* giving place to a parallel versions that grow incompatible over time.
- Interference with commercial networks: a 6G testbed will most likely run in an area where commercial cellular networks operate. As such, it can interfere (see administrative challenges) and be interfered by these networks. The interference from the commercial network may cause errors in the 6G-based location estimations. To avoid this, isolating the network is again a good solution, which can work for indoor environments. Outdoor settings, on the other hand will have more problems, so interference should be considered a limiting factor or even taken into account as a factor that adds realism to the experiments.

C. KEY TAKEOUTS

In this section, the main challenges for implementing a testbed based on the proposed architecture have been reviewed. Administrative challenges are usually the main limitation, but with the proposed architecture, its effects can be alleviated. Nevertheless, some issues, such as licensing or accessing all the capabilities of acquired equipment, can only be solved by establishing partnerships with operators and vendors. Technical challenges mainly stem from the current lack of 6G standards, and can be resolved by using Open RAN and SDR components, and favoring open source over proprietary solutions.

VIII. CONCLUSION

This paper has done a thorough review of the expectations of 6G location in the near future. 6G will bring a slew of new enabling technologies (such as THz communications, RIS, and AI/ML) that will improve the capacity of estimating ranges of the network, and hence, to calculate positions. 6G devices will also benefit from the increasing number of other location technologies, which can be used to further improve location thanks to fusion techniques. Conversely, an increasing number of location aware services will benefit from the location that the 6G network can provide, as well as network functions.

To develop and test these location techniques and location aware applications of the future, the R&D community needs a testbed that is purposefully built for location in 6G. The main requirements of such a platform are that it has to cover all the possible 6G enablers, and do that as 6G technologies are being developed. This is a very challenging task, which can be solved by using as many open components as possible.

The proposed testbed architecture disaggregates the elements into four scopes, each loosely connected to the others, such that they can be upgraded separately as new 6G software is available. These four scopes (physical, network, service, and R&D) have been described in detail, showing examples of the building block implementations that are currently available.

The proposed architecture can be used as a base for a blueprint of a location testbed, resulting in a flexible and future-proof design. An example showing a nomadic testbed based on this architecture has been shown in this paper. This testbed did not have any 6G hardware, since there are no available devices yet, but the development (hardware and software) done for it can be reused once some of the components (namely the terminal and LTE network used in the example) are switched by 6G equipment.

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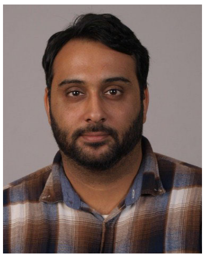

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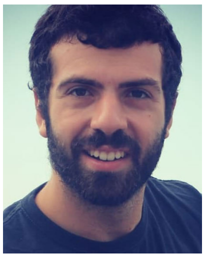

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Capítulo 6

Conclusiones

En este capítulo se resume la investigación realizada en la tesis, y para hacerlo se divide en tres secciones. En la primera Sección, la 6.1, se repasan los objetivos de la tesis y se destacan las principales contribuciones de cada uno. La Sección 6.2 propone algunas posibles líneas de investigación futura relacionadas con la investigación llevada a cabo. Finalmente, en la Sección 6.3 se presenta una lista de publicaciones y otras actividades relacionadas con la tesis.

6.1 Contribuciones

Esta tesis tiene como objetivo mejorar el sistema de localización mediante el uso de diferentes fuentes de información. Con el fin de abordar los diferentes desafíos que existen para una localización precisa en escenarios complejos, se han establecido los objetivos esenciales para superarlos. Se ha establecido un total de seis objetivos que se desarrollan a lo largo de este trabajo. El Obj. 1 está directamente relacionado con el estudio previo y la simulación de fusionar los rangos en el algoritmo de trilateración para comprobar la viabilidad del sistema. Los Obj. 2 y 3 abarcan el desarrollo de un framework para la recogida de datos y su post-procesado para así poder determinar algunas características tanto de las tecnologías asociadas como de los algoritmos utilizados. Los Obj. 4 y 5 proponen diferentes aplicaciones basadas en localización para escenarios complejos como son los escenarios de interior y los de emergencias. Por último, el Obj. 6 define una arquitectura para poder desarrollar pruebas y poder validar algoritmos antes de que la tecnología salga al mercado. A continuación, se expondrán las contribuciones que están relacionadas con cada uno de estos objetivos:

Obj. 1. Estudiar la viabilidad de la fusión de tecnologías en un entorno simulado.

- En primer lugar, en este trabajo se ha llevado a cabo la fusión de diferentes tecnologías con diferentes rangos de precisión. Para ello, se ha simulado un escenario de interior en el que la información de UWB y LTE se han fusionado para poder mejorar la precisión de localización de forma oportunista. Además, se amplía la cobertura en la que se utilizan los rangos precisos de UWB.
- En segundo lugar, se ha propuesto una modificación del protocolo NRPPa para mejorar la integración de una tecnología de alta precisión, en este caso de UWB.
- Por último, se demuestra que el uso de la fusión reduce los costes de despliegue de las tecnologías orientadas a la localización, al reducir la necesidad de un despliegue denso de puntos de referencia.

Obj. 2. Desarrollar un framework para recoger medidas reales de diferentes tecnologías de posicionamiento.

- Para conseguir este objetivo, se ha desarrollado una aplicación móvil capaz de capturar la información del entorno y enviarla a un servidor para procesar la información en tiempo real o en diferido como objetivo del proyecto LOCUS [12]. Esta aplicación es capaz de capturar la información de la red celular, BLE, UWB y WiFi (incluyendo el protocolo 802.11mc).
- Capturar la información del entorno y estudiar las posiciones de los puntos de referencia. Para ello, se han obtenido los planos de los escenarios utilizados y se ha estudiado previamente dónde colocar las posiciones de los puntos de referencia de las diferentes tecnologías para que los experimentos sean más completos, es decir, situaciones de LoS y NLoS, bloqueos y zonas sin cobertura de algunos puntos de referencia, etc. Además, se ha llevado a cabo una planificación de los puntos de referencia de la toma de medidas que han sido obtenidas con precisión centimétrica gracias a medidores láseres y son cruciales para conocer el error asociado a las medidas obtenidas.
- Una vez capturada la información, ésta se envía a un servidor que procesa la información en tiempo real y la almacena para hacer los estudios realizados a lo largo de esta tesis.

Obj. 3. Caracterizar las tecnologías UWB y WiFi en diferentes escenarios.

- A través del framework creado en el objetivo anterior, se han podido almacenar los datos y procesar la información necesaria para caracterizar las tecnologías UWB y WiFi como tecnologías de alta precisión para la localización de usuarios.
- La caracterización de las tecnologías se ha realizado en diferentes escenarios como se ha podido observar a lo largo de las diferentes publicaciones.
- La tecnología UWB es una tecnología de alta precisión muy útil en escenarios con reflexiones en la que es necesario tener visibilidad con el objetivo. De esta manera, su rendimiento en términos de localización es excelente en este tipo de situaciones, consiguiendo precisiones del orden de pocos centímetros. Incluso en escenarios más complejos, la precisión sigue siendo su mejor característica frente a otras tecnologías. Sin embargo, sus capacidades de penetración de obstáculos y su rango de cobertura demostraron su ineficiencia en entornos con una estructura irregular. La limitación del área de cobertura hace que su aplicación sea muy útil para entornos acotados y redes de área personal como es el caso de la realidad virtual.
- La tecnología WiFi FTM basada en el protocolo 802.11mc es una tecnología que ha demostrado ser muy eficiente en muchos ámbitos. En primer lugar, posee una relación entre alcance y precisión bastante interesante ya que permite cubrir áreas grandes como facultades o centros comerciales de manera que permite proveer una localización precisa (con una precisión del orden de los pocos metros) con un despliegue reducido y económico. La implantación del protocolo 802.11mc para proveer de WiFi FTM está altamente integrada en los teléfonos móviles por lo que solamente falta esperar a su incorporación en los routers con dicho protocolo. La gran ventaja del WiFi respecto a UWB es su bajo consumo energético, su implantación a nivel mundial y su constante mejora de nuevos modelos como es ahora WiFi 6.
- Una vez presentadas las ventajas y desventajas de ambas tecnologías, podríamos indicar que el uso dual de ambas tecnologías presenta grandes ventajas y es una tendencia como se muestra gracias a la integración de chips UWB y WiFi FTM cada vez en más dispositivos móviles.

Obj. 4. Proponer un sistema de detección y localización de usuarios en escenarios de emergencia.

- En este trabajo se ha investigado acerca de diferentes tecnologías para la detección y localización como son la tecnología celular, BLE, UWB y WiFi, y se han propuesto las dos últimas como aquellas que ofrecen mejores características para la localización de víctimas bajo escombros. En este estudio se propone un protocolo de comunicación como una extensión del protocolo NRPPa para mejorar la comunicación entre los servicios de rescate y los servicios o aplicaciones de localización de víctimas.
- El sistema de detección y localización propuesto para rescatar víctimas que se encuentren inconscientes o atrapadas bajo escombros tiene un gran potencial ya que en escenarios con derrumbamientos, asumimos que los únicos dispositivos que están disponibles para su detección son aquellos que no necesitan estar conectados a la red eléctrica, es decir, móviles y pulseras inteligentes. Este tipo de dispositivos siempre suelen llevarse encima por lo que nos indica la posición directa de las víctimas. Además, todas las interferencias y posibles detecciones creadas por otros dispositivos (por ejemplo, televisiones inteligentes, asistentes de casa, altavoces inteligentes o incluso los routers de las casas/oficinas) se anulan gracias a la caída de la corriente dentro del área afectada.
- El sistema propuesto es una simplificación completa de un escenario de emergencia pero que nos permite comprobar las ventajas que tienen las diferentes tecnologías para la localización y detección. Un dron que sobrevuele un área de emergencias, gracias a que es independiente de la superficie, puede cubrir grandes cantidades de terrenos en pocos minutos. Lo que permite obtener un sistema capaz de detectar y localizar múltiples víctimas de forma rápida y en un área extensa.

Obj. 5. Estudiar y proponer una aplicación basada localización para una educación inteligente.

- El uso de los servicios basados en la localización para la educación es cada vez más frecuente con la implantación de servicios como la realidad extendidad o la navegación a través de grandes instituciones educativas. El impacto de las tecnologías 5G y WiFi en el ámbito educativo es de gran importancia, ya que tienen el potencial de transformar la manera en que los estudiantes aprenden y se relacionan con su entorno en este sector.

- Tras mostrar en una visión general de algunos servicios basados en localización que se utilizarán en el futuro, se ha llevado a cabo una prueba de concepto para automatizar el control de asistencia en entornos educativos. El sistema propuesto puede implementarse fácilmente en instituciones educativas, ofreciendo un método sencillo y no intrusivo para mejorar la eficiencia de la enseñanza y el aprendizaje. El proceso de control de asistencia se puede realizar a través de los dispositivos móviles de los alumnos, ya que todos ellos disponen de tecnología móvil y WiFi. Además, los datos del sistema pueden analizarse para identificar patrones de asistencia, lo que permite a los profesores optimizar la programación y la impartición de las clases.

Obj. 6. Evaluar la localización en escenarios de interior con mapas incompletos.

- Uno de los mayores inconvenientes que sufren los sistemas de localización basados en mapas radio es el coste asociado a la recogida de datos para la fase de entrenamiento y futuros reentrenamientos. Por ello, el uso de modelos de ML nos permite reducir en gran medida el número de puntos necesarios para modelar un escenario concreto.
- Tras estudiar diversos algoritmos de localización basados en modelos, se ha llevado a cabo un experimento real en la que se observa cómo se degradan los algoritmos basados en mapas radio y los basados en modelos a medida que se van reduciendo el número de puntos de entrenamiento hasta el 20%.
- Los sistemas basados en modelos en escenarios que cumplan las mismas características físicas permiten que los modelos de localización sean extrapolables y se permita la escalabilidad de los servicios.

Obj. 7. Proponer una arquitectura flexible para comprobar la viabilidad de algoritmos basados en localización.

- Se ha descubierto que no existe una arquitectura o diseño estándar para verificar las diferentes tecnologías o técnicas para los servicios de localización. Por tanto, se presenta una arquitectura flexible para poder abarcar el futuro de la tecnología dentro de un marco preestablecido y, poder así, llevar a cabo pruebas estandarizadas al igual que se realizan para poder sacar un producto al mercado.

- El trabajo estudia las necesidades que existen en los futuros servicios móviles dependientes de la localización y las soluciones técnicas que puede aportar la futura red 6G. Se propone una metodología que permita verificar en una fase temprana las técnicas y algoritmos propuestos, y evaluar su respuesta a las necesidades de los servicios.

6.2 Trabajo Futuro

Algunas posibles líneas de investigación que podrían dar continuidad al estudio realizado en esta tesis son las siguientes:

- Desarrollo e investigación para una localización cooperativa en la que distintos UEs combinen su información [126] usando diversas tecnologías radio basada en multitecnología. Para este estudio, se deben crear protocolos de comunicación entre dispositivos de diversa naturaleza de las que se pueda obtener la posición de dicho dispositivo en relación con su contexto. Dicha información se puede verter a la red celular y realizar el cálculo de la localización de los diferentes dispositivos en la nube. Gracias a este tipo de cálculos, se permite conocer de manera ubicua la posición de los diferentes dispositivos sin necesidad de densos despliegues de una sola tecnología.

- La creación de un prototipo para llevar a la realidad el sistema de detección y localización de víctimas en escenarios de emergencia. El primer estudio de escenarios de emergencias [127] avala la necesidad de la creación de un sistema que permita un mapeo rápido y preciso para detectar y localizar víctimas tras una catástrofe. Diferentes tecnologías se pueden aplicar en este sistema como son los sensores térmicos, lidar o 5G, además de los ya mencionados en el artículo como son UWB, BLE y WiFi.

- Caracterizar la red 5G con medidas de marcas temporales. Debido a la fase temprana de 5G durante el desarrollo de esta tesis, no se han conseguido obtener marcas temporales como se indica en el 3GPP con multi-RTT [128]. Para ello habría que modificar mínimamente el framework ya desarrollado durante esta tesis para conseguir capturar dichos datos.

- Uso de la inteligencia artificial para estimar aquellas fuentes precisas que se encuentren en visión directa en los escenarios de interior. De esta forma, se busca realizar un pesado óptimo de las diferentes fuentes de información que nos proveen diferentes tecnologías. Para el caso de la fusión de las tecnologías, hay tres tecnologías que se postulan como predominantes en la localización precisa en escenario de interior que son 5G, UWB y WiFi. Estas tecnologías ya se encuentran integradas en los dispositivos móviles más modernos. Por tanto, en unos años, los dispositivos móviles se encontrarán rodeados de fuentes de información precisa y el objetivo será conocer el estado de aquellas fuentes de información que tengan mejores condiciones de propagación para reducir el error de posicionamiento.

6.3 Resultados

El trabajo llevado a cabo durante esta tesis ha dado lugar a diversas contribuciones que se sintetizan en las siguientes secciones.

6.3.1 Publicaciones en revistas

Publicaciones derivadas de esta tesis

El trabajo realizado en esta tesis ha dado lugar a cinco artículos publicados en revistas de alto impacto más otras dos en proceso de revisión, que se enumeran a continuación:

[I] CS Alvarez-Merino, HQ Luo-Chen, EJ Khatib and R Barco, "Opportunistic fusion of ranges from different sources for indoor positioning," *IEEE Communications Letters* 25 (7), 2260-2264, 2021.

[II] CS Alvarez-Merino, HQ Luo-Chen, EJ Khatib and R Barco, "WiFi FTM, UWB and Cellular-Based Radio Fusion for Indoor Positioning," *Sensors* 21 (21), 7020, 2021.

[III] CS Alvarez-Merino, EJ Khatib, HQ Luo-Chen, JL Michel, S Casalderrey-Díaz, J Alonso and R Barco, "WiFi FTM and UWB Characterization for Localization in Construction Sites," *Sensors* 22(14), 5373, 2022.

[IV] CS Alvarez-Merino, EJ Khatib, HQ Luo-Chen and R Barco, "Victim Detection and Localization in Emergencies," *Sensors* 22 (21), 8433, 2022.

[V] EJ Khatib, CS Alvarez-Merino, HQ Luo-Chen and R Barco, "Designing a 6G testbed for location: use cases, challenges, enablers and requirements," *IEEE Access* 11, 10053 - 10091, 2023.

[VI] CS Alvarez-Merino, EJ Khatib, HQ Luo-Chen, A Tarrías Muñoz and R Barco, "Evaluation and Comparison of 5G, WiFi and fusion when incomplete maps for Indoor Localization," *IEEE Access*, *Under Review.*

[VII] CS Alvarez-Merino, EJ Khatib, A Tarrías Muñoz and R Barco, "Exploring Indoor Localization for Smart Education," *IEEE Transactions on Learning Technologies*, *Under Review.*

Además, se ha contribuido directamente a la publicación de un capítulo de un libro.

[VIII] S. Bartoletti, C. S. Alvarez-Merino, R. Barco, H. Chen, A. Conti, Y. Filippas, D. Giustiniano, C. A. G. Vega, M. Hunukumbure, F. Jiang et al., "Positioning methods," Positioning and Location-based Analytics in 5G and Beyond, 2023

Publicaciones en revistas relacionadas con esta tesis

Paralelamente, el autor ha colaborado en proyectos de investigación a los que ha contribuido y que han dado lugar a varias publicaciones en revistas indexadas.

[IX] HQ Luo-Chen, CS Alvarez-Merino, EJ Khatib and R Barco, "Method for Artificial KPI Generation With Realistic Time-Dependent Behaviour," *IEEE Communications Letters* 25 (9), 2978-2982, 2021.

[X] J Mendoza, I de-la-Bandera, CS Álvarez-Merino, EJ Khatib, J Alonso, S Casalderrey-Díaz and R Barco, "5G for Construction: Use Cases and Solutions," *Electronics* 10 (14), 1713, 2021.

6.3.2 Conferencias y workshops

Conferencias

También se han presentado varios trabajos en congresos nacionales e internacionales, como se muestra a continuación.

[XI] CS Alvarez-Merino, HQ Luo-Chen, EJ Khatib and R Barco, "Fusion of LTE and UWB ranges for trilateration," *XXXV Simposium Nacional de la Unión Científica Internacional de Radio, Malaga, 2020.*

[XII] CS Alvarez-Merino, HQ Luo-Chen, EJ Khatib and R Barco, "Aplicación móvil para localización de interior mediante fusión de tecnologías," *XXXVI Simposium Nacional de la Unión Científica Internacional de Radio, Vigo, 2021.*

[XIII] CS Alvarez-Merino, AT Muñoz, HQ Luo-Chen, EJ Khatib and R Barco, "Posicionamiento 5G con mapas radio incompletos," *XXXVII Simposium Nacional de la Unión Científica Internacional de Radio, Cáceres, 2023.*

[XIV] CS Alvarez-Merino, "Demostración de localización de usuarios en tiempo real mediante la fusión de las tecnologías 4G y Wi-Fi, y la tecnología emergente UWB," *1ª edición de Mobile Week, Málaga, 2021.*

[XV] CS Alvarez-Merino, HQ Luo-Chen, JL Michel, EJ Khatib and R Barco, "UWB and WiFi characterization for localization in construction sites," *INTERACT 2nd MC and 1st Technical Meetings, Bolonia, 2022.*

[XVI] CS Alvarez-Merino, "La localización del futuro en el 6G," *2ª edición de Mobile Week, Málaga, 2022.*

Otras Conferencias

[XVII] HQ Luo Chen, CS Álvarez-Merino, EJ Khatib and R Barco, "Time-dependent KPI generation based on Copula," *XXXV Simposium Nacional de la Unión Científica Internacional de Radio, Malaga, 2020.*

[XVIII] HQ Luo Chen, CS Álvarez-Merino, JC Baena González, EJ Khatib, R Barco, "Herramienta de diagnosis para redes móviles basada en puntos sigmas de correlaciones," *XXXVI Simposium Nacional de la Unión Científica Internacional de Radio, Vigo, 2021.*

[XIX] HQ Luo Chen, EJ Khatib, CS Álvarez-Merino, JC Baena González and R Barco, "Detección de degradaciones en redes móviles basado en máquina de estados y umbrales de Otsu," *XXXVII Simposium Nacional de la Unión Científica Internacional de Radio, Málaga, 2022.*

6.3.3 Proyectos relacionados

Esta tesis ha sido parcialmente financiada por los siguientes proyectos:

- Proyectos Internacionales:
  - Proyecto LOCUS (8.06.25/59.8062), Unión Europea, Proyectos Horizonte 2020. Número de la ayuda No.871249 en fondos de Investigación e Innovación [12].
- Proyectos Nacionales:
  - Proyecto Maori sobre Gestión inteligente de recursos radio en open radio b5G/6G (TSI-063000-2021-53), Ministerio de Asuntos Económicos y Transformación Digital, Plan de Recuperación, Transformación y Resiliencia [15].
  - TEDES-5G: Técnicas 5G para una Edificación Eficiente y Segura (UMA-CEIATECH-12), Universidad de Málaga, Energías renovables, eficiencia energética y construcción sostenible [13].
  - PENTA P18-FR-4647 Proyectos de investigación en colaboración con el tejido productivo [14].
  - Proyecto NEREA (RTC-2017-6661-7), Ministerio de Ciencia, Innovación y Universidades – Agencia Estatal de Investigación, Fondos FEDER [129].

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