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TESIS DOCTORAL

NUEVOS SISTEMAS DE LOCALIZACIÓN INDOOR DE DISPOSITIVOS IOT
(LINDIOT)

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- [2] **J. A. López-Pastor**, A. Gómez-Alcaraz, D. Cañete-Rebenaque, A. S. Martinez-Sala and J. L. Gómez-Tornero, "Near-Field Monopulse DoA Estimation for Angle-Sensitive Proximity WiFi Readers," in *IEEE Access*, vol. 7, pp. 88450-88460, 2019, doi: 10.1109/ACCESS.2019.2925739.
- [3] **J. A. López-Pastor**, P. Arques-Lara, J. J. Franco-Peñaranda, A. J. García-Sánchez and J. L. Gómez-Tornero, "Wi-Fi RTT-Based Active Monopulse RADAR for Single Access Point Localization," in *IEEE Access*, vol. 9, pp. 34755-34766, 2021, doi: 10.1109/ACCESS.2021.3062085.
- [4] **J. A. López-Pastor**, A. J. Ruiz-Ruiz, A. J. García-Sánchez, and J. L. Gómez-Tornero, "An automatized contextual marketing system based on a wi-fi indoor positioning system," *Sensors*, vol. 21, no. 10, pp. 1–26, 2021.

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Mención de Doctorado Industrial

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Resumen

Los sistemas de localización de los dispositivos que forman el Internet de las Cosas (IoT) se basan, habitualmente, en sistemas satelitales (GNSS). Sin embargo, debido a la dificultad que tienen las ondas electromagnéticas de atravesar las paredes y techos de los edificios, los sistemas satelitales no ofrecen una precisión adecuada en interiores de edificios. Por lo tanto, no pueden ser empleados en aplicaciones como localización, navegación o guiado de personas en estos entornos.

Al no poder emplearse los sistemas de localización satelitales, se han desarrollado diversas propuestas, algunas propietarias y otras de ámbito científico, que permiten la localización de dispositivos IoT en entornos *indoor*. Estas propuestas emplean tecnologías tan diversas como imagen, radiofrecuencia, sensores inerciales, sensores de campo magnético, e incluso señales acústicas. En esta tesis nos centraremos en los sistemas basados en radiofrecuencia, dado que se trata de los más ampliamente utilizados. Dentro de los sistemas basados en radiofrecuencia, dependiendo de la infraestructura empleada y del propósito del mismo, se pueden emplear diferentes tecnologías para su funcionamiento, entre ellas destacan: WiFi, Zigbee, UWB o Bluetooth Low Energy.

La tecnología WiFi ha sido una de las predominantes a la hora de implementar los sistemas de localización en interiores, sobre todo en grandes edificios con gran número de visitantes como son aeropuertos, centros comerciales, museos, etc. Esto se debe a que en este tipo de instalaciones suele existir una amplia red WiFi desplegada para dotar de conectividad a los visitantes. Esta red puede ser empleada a su vez para la generación de sistemas de localización, ahorrando así el despliegue de nueva infraestructura. Se ha de tener cuenta que el coste del despliegue de infraestructura, incluyendo equipos, cableado, ingeniería, etc., suele ser una de las tareas más costosas dentro de cualquier proyecto de ingeniería. Es por ello que se tiende a reutilizar las redes WiFi existentes dotándolas de otras funcionalidades, además de la propia de conectividad.

Una de las principales clasificaciones de los sistemas de localización suele dividir a los mismos entre sistemas activos y pasivos. Los sistemas activos requieren la intervención del dispositivo a localizar mediante una aplicación y/o proceso que recoge información del espectro RF a su alcance, mientras que los sistemas pasivos recogen la señal RF de los dispositivos IoT que detectan, pero no requieren de su participación. Durante el desarrollo de esta tesis se ha trabajado en los dos tipos de sistemas, estando dividida la investigación en dos partes claramente diferenciadas.

En la primera parte de la tesis se ha trabajado en los sistemas de localización pasivos, concretamente en sistemas de localización mediante la técnica conocida como radar monopulso empleando el estándar WiFi 802.11. Posteriormente se trabajó en la técnica radar monopulso en campo cercano y, a continuación, se combinó con sistemas de ranging basados en el estándar 802.11mc. Mediante la combinación de ambas tecnologías se generó un sistema de localización empleando

un único punto de acceso (AP). Por último, el trabajo final de este bloque empleó antenas de haz con escaneo en frecuencia, técnicas de *channel-hopping* y el algoritmo MUSIC para ampliar el FoV de los dispositivos pasivos implementados en el trabajo anterior. En la segunda parte de la tesis se ha trabajado en la implementación de un IPS (Indoor Positioning System) de *smartphones* para grandes superficies, empleando únicamente los APs que ya se encuentran instalados y con una precisión zonal a nivel tienda/pasillo. El IPS es una de las piezas fundamentales de un mecanismo mayor conocido como Sistema de Marketing Contextual. Junto con la descripción detallada del IPS, se explican todos los componentes e intercambios de información entre los diferentes bloques que forman el Sistema de Marketing Contextual.

Abstract

The location and positioning systems involved in the Internet of the Things (IoT) paradigm are generally based on satellite systems (GNSS). However, because the electromagnetic waves have difficulties getting through the walls and roof of the buildings, the satellite systems do not have enough accuracy indoors. Therefore, this kind of system cannot be employed in the location and navigation of IoT devices or people indoor.

Because satellite tracking systems cannot be employed, several proposals are focused on overcoming the indoor location of IoT devices. Some proposals are from the scientific area, and some other proposals are proprietary. These proposals employ different technologies like image-based, radiofrequency, inertial sensors, magnetic field sensors, and acoustic signals. This Ph.D. thesis will focus on radio frequency-based systems because they are the most frequently used. Among the radio frequency-based systems, several technologies can be employed according to the infrastructure employed and the purpose of the project. These technologies are WiFi, Zigbee, UWB, or Bluetooth Low Energy.

WiFi technology has been one of the most employed in indoor location systems, particularly in large infrastructures with a high number of visitors such as airports, malls, museums, etc. This is mainly because there is often a wide WiFi network already deployed to provide connectivity to visitors in this kind of infrastructure. This network could also be employed to implement the location system, saving savings in deploying the system. It should be taken into consideration that the main cost of any project is the infrastructure deployment phase, where the wiring and the new equipment acquisition are carried out. Because of the aforementioned costs, the WiFi networks are often reused with other applications than the data connectivity.

One of the main classifications of the indoor location system usually divides them into active and passive. The active systems require the participation of the device to be located by using an app that collects the data from the RF within the range. However, the passive systems collect the RF signal of the IoT devices within the range but do not require their involvement. In this thesis, we have worked on the two kinds of systems. In the first chapters, we have worked in the passive location systems, mainly in the WiFi RADAR monopulse function-based systems based on the 802.11 standard. Next, we focused on the near-field monopulse technique, and later we merged this technique with a ranging system based on the 802.11mc standard. The last work of this section employed a frequency beam antenna with channel-hopping techniques and the MUSIC algorithm to increase the FoV of the previously implemented devices. In the following chapters, we work on implementing a smartphone Indoor Positioning System (IPS) for large infrastructures. One of the main premises of our IPS is the use of the already deployed APs with zonal accuracy. The

IPS is one of the key enabling technologies of a Marketing Contextual System. Moreover, the component and information flows between the different blocks that make up the Contextual Marketing System are explained.

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Capítulo 1

Introducción y objetivos

1.1 Introducción.

Los sistemas de localización de dispositivos que se engloban dentro de paradigma de Internet de las Cosas (IoT) están alcanzando una alta popularidad en años recientes [7], tanto en el ámbito de la investigación como entornos industriales y comerciales. Cuando se pretende implementar un sistema de localización de dispositivos IoT en entornos *outdoor* se suele emplear un Sistema Global de Navegación Satélite (GNSS). Los sistemas GNSS cubren la mayoría de necesidades de los sistemas de localización en estos entornos, como son el posicionamiento, la navegación y guiado de objetos y/o personas, siendo un estándar común y de fácil implementación. Sin embargo, debido a la dificultad que tienen las ondas electromagnéticas de atravesar el techo y las paredes de los edificios, los sistemas de localización basados en GNSS no ofrecen una buena precisión en el interior de edificios. Por ello, cuando se desea establecer cualquier sistema de localización de dispositivos IoT en entornos *indoor* se suele emplear otro tipo de tecnologías, no existiendo ningún estándar ni tecnología que cubra todas las necesidades. Por lo tanto, ante cada proyecto o necesidad de despliegue de un sistema de localización *indoor* se escoge la tecnología que mejor se adapte a los requerimientos concretos. De este modo, existen sistemas de localización *indoor* basados en visión, en radiofrecuencia, otros que emplean sensores inerciales (brújula, acelerómetro, compas, etc), sistemas basados en sensores de campo magnético e incluso otros que emplean ondas acústicas. En el ámbito de la robótica, es común que los sistemas de localización, navegación y guiado se generen mediante técnicas de visión estereoscópica, técnicas SLAM y radar LIDAR [8].

Con respecto a los ámbitos de aplicación de los sistemas de localización de dispositivos IoT en entornos *indoor*, hay un gran número de ellos. A modo de ejemplo, algunos de los servicios que se ofrecen mediante este tipo de sistemas comprenden desde el guiado a través de grandes y complejos edificios como puede ser en entornos aeroportuarios, hasta soluciones de marketing contextual desplegadas en entornos de retail o centros comerciales. Otros ámbitos en los que se han desarrollado soluciones de localización *indoor* con éxito son los sistemas de gestión hospitalarios, gestión de edificios y ciudades inteligentes (*Smart cities* y *Smart buildings*) [9], diseño de sistemas de vigilancia y gestión de *Smart Grids* [10]. Con respecto a la localización de personas, a menudo se asocia la localización y gestión de *smartphones* directamente a la localización de personas. Debido a su gran proliferación, ya que la mayoría de personas lleva consigo uno, o incluso varios, si un sistema es capaz de detectar la presencia y movimientos de dispositivos IoT del tipo *smartphone*, se puede decir que el sistema es capaz de detectar el movimiento de las personas. Además, gracias a los servicios de localización sobre smartphones y a las capacidades de los mismos, se puede ofrecer multitud de otros servicios de valor añadido para los usuarios de grandes instalaciones. En la Figura 1 se muestra, a modo de ejemplo, diferentes aplicaciones de los sistemas de localización *indoor*.

Figura 1. Diferentes aplicaciones de sistemas de localización indoor. a) Aplicado a localización de personas y objetos en museos b) Sistema de localización en entorno industrial c) Sistema de navegación y guiado en un aeropuerto

Debido al carácter eminentemente práctico de esta tesis, en este trabajo nos centramos en los sistemas de localización basados en radiofrecuencia, dado que se trata de los más extendidos y de los que mayor ámbito de aplicación presentan. Las tecnologías de radiofrecuencia que se suelen emplear para generar estos sistemas son: WiFi, Bluetooth, Bluetooth Low Energy (BLE), Zigbee o UWB [11]. De entre todas estas tecnologías, cuando se trata de establecer un sistema de localización de dispositivos IoT en grandes instalaciones como museos, aeropuertos, centros comerciales, etc., se suele emplear tecnología WiFi [12]. Esto es debido a que en este tipo de infraestructuras ya cuentan con una amplia red de Access Point previamente instalados con el fin para dotar a los visitantes y trabajadores de conectividad. Esa misma red WiFi puede ser reutilizada y empleada para establecer el sistema de posicionamiento *indoor*. Se consigue así evitar el despliegue de infraestructura necesario para generar el espectro electromagnético empleado en el sistema de localización. Es de destacar que el coste de despliegue de infraestructura es una de las tareas con mayor envergadura en cualquier proyecto de ingeniería. El despliegue de infraestructura requiere, entre otras tareas, de la realización de un proyecto de ingeniería, de llevar a cabo el cableado de los edificios, del aprovisionamiento y la instalación de equipos, y de la puesta en marcha del sistema. Tal y como se puede deducir, además, cuanto mayor sea el tamaño de los edificios donde se desea desplegar el sistema, mayor será el coste de la instalación.

Una clasificación habitual de los sistemas de localización *indoor* es en relación a la componente RF de la señal WiFi que se emplea para generar el sistema. Se suelen clasificar entre los basados en *fingerprinting* (FP), que emplean la RSSI (Received Signal Strength Indicator) como métrica, los sistemas *Time of Arrival* (ToA), que se basan en el cálculo de la distancia hasta el dispositivo a localizar y, por otro lado, se encuentran los sistemas que calculan el *Direction of Arrival* (DoA o AoA) del dispositivo a localizar. En la Figura 2 se muestra un ejemplo de funcionamiento de este tipo de dispositivos.

Figura 2. Izq) Esquema de funcionamiento de sistema de localización indoor basado en RSSI; Centro) Sistema basado en ToA; Dcha) Sistema que emplea DoA

Otro tipo de clasificación de los sistemas de localización *indoor* se suele realizar con respecto a quien es el encargado de adquirir la métrica que se emplea en el algoritmo. Si el dispositivo IoT es el encargado de adquirir la métrica empleada en la localización, se llaman “sistemas activos”, mientras que si el dispositivo IoT es localizado y no lleva a cabo la adquisición de los datos, el sistema generado es llamado “sistema pasivo”. En el capítulo siguiente se describe con detalle la clasificación de los sistemas de localización de dispositivos IoT, así como las principales ventajas e inconvenientes de cada uno de ellos. Esta descripción y análisis se realiza con el fin de explicar con detalle el contexto en el que se enmarca esta tesis, así como facilitar la comprensión de sus objetivos y contribuciones.

Por último, se detalla a continuación el contenido del resto de capítulos de esta tesis. En lo que resta de capítulo describiremos las diferentes clasificaciones de los sistemas de localización con el fin de dar un contexto al lector del documento, para posteriormente destacar las contribuciones de esta tesis. En el Capítulo 2 se presentan los artículos publicados. En el Capítulo 3 se comentan y detallan cada uno de los artículos enunciados en el capítulo anterior. Por último, en el Capítulo 4 se presentan las conclusiones y las posibles líneas futuras.

1.2 Contexto. Clasificación de los sistemas de localización.

Dentro de las distintas clasificaciones que podemos encontrar en la bibliografía de los sistemas de localización *indoor* de dispositivos IoT, primero nos centraremos en la clasificación entre sistemas activos y pasivos. Posteriormente se detallará las características de los sistemas de localización que permiten su clasificación entre sistemas del tipo *Time of Arrival* (ToA), *Angle of Arrival* (AoA) o los basados en la métrica RSSI (*Received Signal Strength Indicator*).

Centrándonos en la clasificación de sistemas de localización WiFi entre sistemas activos y sistemas pasivos [13], cuando se quiere localizar en un entorno *indoor* a un dispositivo IoT, se llama al sistema de localización “activo” si el dispositivo es el encargado de buscar y recoger la información sobre los AP que tiene a su alrededor y de enviarla hasta un servidor donde se implementa el algoritmo de localización. Trasladando este escenario a una persona transportando un *smartphone*, en un sistema de localización activo el *smartphone* es el encargado de escanear las redes WiFi que tiene a su alrededor cuando se encuentra en un edificio donde desea ser localizado. La información recogida, que puede ser la RSSI de cada uno de los APs, la dirección MAC de los APs detectados u otro parámetro, es enviado al servidor remoto donde se encuentra implementado el algoritmo de localización.

Por el contrario, cuando se habla de un sistema de localización pasivo, son los APs instalados los que se encargan de recoger los parámetros de la señal RF del dispositivo IoT. Continuando con el escenario de una persona transportando un *smartphone* en el interior de un edificio, en este tipo de sistemas, son los APs los que se encargan de la tarea de detectar el parámetro de la señal RF a utilizar en los algoritmos de localización. En este caso, en un entorno WiFi, los *smartphones*, y en general cualquier dispositivo IoT equipado con una interfaz WiFi, emiten con bastante frecuencia tramas del protocolo 802.11 para detectar los APs en su entorno. Este mecanismo es empleado para detectar los APs dentro del alcance. Estas tramas son detectadas y empleadas por los APs, los cuales las procesan y mandan al servidor de localización para determinar la posición del *smartphone*.

Cada uno de estos dos tipos de sistemas tienen unas ventajas e inconvenientes con respecto a la participación del usuario, precisión, escalabilidad y velocidad de despliegue. Centrándonos en los sistemas de localización de *smartphones*, que es el objeto de la tesis, los sistemas de localización activos tienen la desventaja de que requieren de la participación de los usuarios. Los *smartphones* por sí solos no son capaces de escanear los AP ni de enviar la información a los servidores donde se implementan los algoritmos de localización, por lo que se requiere de la instalación de una app que lleve a cabo estas tareas. Mediante esta app, de forma periódica, se escanean los APs a su alrededor, se obtiene la métrica de interés (comúnmente RSSI), se procesa la información obtenida y, por último, realiza el envío de la información al servidor donde se realiza la tarea de localización. Por el contrario, tienen la ventaja de que una vez localizado e identificado el dispositivo se puede interactuar con él. Es decir, al ser una aplicación instalada en un *smartphone*, sobre el servicio de localización se pueden implementar otra serie de

funcionalidades relacionadas con marketing contextual, guiado y navegación, etc. Además, aunque supone un uso más intensivo de la batería, se puede hacer uso de los sensores inerciales y otro tipo de sensores del dispositivo que permiten obtener una mejora en la precisión del sistema de localización. Hoy en día la mayoría de smartphones están dotados de sensores inerciales como acelerómetros, brújula, sensor de campo magnético, etc. Mediante la combinación de la información obtenida de las redes WiFi junto con la información extraída de los sensores inerciales se pueden generar sistemas de localización *indoor* con una precisión de centímetros.

Si nos centramos en el sistema operativo de los *smartphones*, solamente los terminales de tipo Android ofrecen a los programadores la capacidad de acceder a los parámetros de las redes WiFi a través de interfaces de programación dentro de su sistema operativo. Por el contrario, los dispositivos con sistema operativo iOS tienen limitada esta funcionalidad y no permiten a los programadores conocer ningún parámetro de las redes WiFi que se detectan en su entorno. Por lo tanto, los sistemas de localización activos se pueden implementar en cualquier dispositivo IoT que se pueda programar y en *smartphones* Android, estando restringido su uso en *smartphones* con iOS.

Con respecto a las ventajas e inconvenientes que presentan los sistemas de localización pasivos, su principal ventaja es que no necesitan de la intervención de los usuarios para su localización. Esto se debe a que las tramas empleadas por los APs para realizar la localización de los dispositivos son enviadas independientemente de las aplicaciones instaladas y de forma periódica por los smartphones, tal y como se ha comentado anteriormente. Al ser independiente del sistema operativo del dispositivo, tanto los terminales Android como iOS pueden ser localizados con este tipo de sistema. Sin embargo, las técnicas de *randomizado* de direcciones MAC, implementada en las últimas versiones tanto de Android [14] como de iOS [15], impiden identificar de forma unívoca este dispositivo a lo largo de todo el recorrido por el interior de un edificio. Con respecto a los inconvenientes, para la instalación de este tipo de sistema, se requiere de la instalación de APs capaces de realizar las tareas de localización o bien de la modificación de los APs existentes. Se debe tener en cuenta que la instalación de nuevos APs es, a menudo, una tarea difícil de abordar dentro de un edificio de gran tamaño.

Nos centraremos a continuación en la clasificación de sistemas basados en *fingerprinting*, ToA y AoA. Cuando se habla de sistemas basados en la técnica conocida como *fingerprinting*, se suele hablar de sistemas basados en la adquisición de RSSI. Aunque también se puede realizar *fingerprinting* de otro tipo de datos, como, por ejemplo, de campo magnético, son mucho menos empleados que los basados en *fingerprinting* de RSSI. Este tipo de sistemas ha tenido una alta popularidad [16] en los últimos años para la implementación de sistemas de localización de dispositivos IoT, incluyendo *smartphones*, debido a que cualquier interfaz de red WiFi 802.11 devuelve los valores de RSSI de los APs dentro del alcance. Estos valores son accesibles, por lo tanto, de una forma sencilla en todo tipo de dispositivos excepto

en smartphones con el sistema operativo iOS. A modo de resumen, la implementación de un sistema de *fingerprinting* se basa en una fase inicial donde se realiza una calibración de la zona donde se desea instalar el sistema de localización y la generación de un modelo a través del cual se asocia un determinado nivel de RSSI a una determinada zona. Tal y como se comentaba anteriormente, se ha tratado de una de las formas de localización *indoor* más habitual, y se pueden encontrar en la literatura científica diversos trabajos que emplean esta técnica [17], [18]. Las diferencias entre estos trabajos radican en la forma de llevar a cabo la calibración de la superficie donde se desea localizar los dispositivos, los algoritmos empleados para realizar la localización, el preprocesamiento realizado a las RSSI adquiridas y, por último, la aplicación de modelos de movimiento que doten de una mayor fiabilidad los resultados obtenidos por los algoritmos de localización. Una de las principales desventajas de los sistemas basados en *fingerprint* son que requieren de una fase de calibración que puede requerir de bastante tiempo [19]. Esto se debe a que se tiene que recoger un *fingerprint* característico de cada una de las posiciones o zonas donde se desea localizar. Además, esta tarea de calibración se tiene que realizar de forma periódica, dado que el *fingerprint* varía con el tiempo a medida que los AP son movidos de sitio, cambiados por otros modelos, se producen cambios en la distribución del edificio o nuevos APs son instalados [5].

Los sistemas de localización basados en *Time of Arrival* (ToA) se basan en calcular la posición de un dispositivo en base a la distancia entre el dispositivo a localizar y tres o más APs. Para el cálculo de la distancia se suele emplear el *Time-of-flight* de la señal [20]. A efectos prácticos, este tiempo se obtiene a través del Channel State Information (CSI) ofrecido por el chipset de las tarjetas WiFi y es convertido en distancia empleando la velocidad de propagación de la señal RF. Cuando se conoce la distancia desde el dispositivo a al menos 3 APs, empleando técnicas de triangulación se puede calcular la posición con precisión. Se trata de una técnica ampliamente empleada en tecnología con un gran ancho de banda, como puede ser UWB, pero que sin embargo no ha obtenido una gran popularidad en sistemas WiFi. Esto se debe a que su precisión disminuye a medida que la componente multipath introducida por el entorno crece [21] y que, por otro lado, debido a que la velocidad de propagación de la señal RF es cercana a la velocidad de la luz, un pequeño fallo en la estimación del time-of-flight causa un error en la estimación de la distancia de varios metros. Además, el acceso a la información del CSI/IQ requerido para calcular el *Time of flight*, a menudo, no es directamente accesible por el hardware comercial. Por lo tanto, requiere de modificaciones del hardware y/o del software de los APs para poder medir el tiempo de propagación.

Con respecto a los sistemas del tipo *Angle of Arrival* (AoA), se caracterizan por determinar el ángulo con respecto del AP de la señal RF del dispositivo que se pretende localizar. Para poder estimar con éxito el ángulo, podemos encontrar dos tipos de sistemas claramente diferenciados. El enfoque tradicional es emplear *arrays* de antenas que tienen que ser sincronizadas para calcular el retardo en recibir la señal por cada una de ellas. Otro tipo de mecanismos tradicionales para detectar el AoA es

emplear un tipo de antena específicos designados para tal efecto, como son las llamadas Switched Beam Antenna o las Revolving Antenna controladas mecánicamente. Estas antenas tienen el inconveniente de que necesitan sistemas complejos para su gestión. Además, junto con estas estructuras complejas de antenas, se suele necesitar de técnicas de procesamiento de la señal basados en la IQ de la señal RF [22]–[24]. Habitualmente, este tipo de información no es accesible desde los APs comerciales por lo que se tiene que realizar modificaciones ad-hoc de los APs con el fin de proveer de esta información. Sin embargo, tal y como explicaremos en los siguientes capítulos de este trabajo, hay un nuevo enfoque para la estimación del AoA empleando RSSI. Este nuevo paradigma es capaz de calcular el AoA mediante hardware comercial y sin necesidad de acceder a la información compleja de la señal. Para ello se requiere el empleo de antenas directivas en la conocida como configuración monopolso.

1.3 Contribuciones

1.3.1 Empleo de la Función Monopulso en sistemas de localización de dispositivos IoT

Tal y como se ha comentado en la sección anterior, los sistemas del tipo AoA requieren del empleo de un tipo de antena *ad-hoc* para las tareas de localización, o bien requieren de un procesamiento de señal basados en la componente compleja de las señales transmitidas que no es común en los sistemas de comunicaciones comerciales.

Con el fin de hacer frente a estas limitaciones, como primera contribución se diseña una arquitectura Híbrida Analógica Digital (HAD) que, basada en RSSI, es decir, sin hacer uso de información IQ de la señal, es capaz de determinar el AoA de un dispositivo IoT. La componente hardware del sistema está basado en un AP comercial dotado con un chipset MiMo y dos antenas directivas situadas en configuración monopolso. Mediante la adquisición de una RSSI diferente por cada una de las antenas y el empleo de la Función Monopulso se puede determinar con exactitud el ángulo del dispositivo a localizar. El sistema está basado en concepto de radar MiMo monopolso [25]–[27], pero a diferencia de los trabajos previos, no se emplean procesamiento de la señal RF analógica, sino que empleamos la RSSI de la señal digital para la estimación del ángulo.

Una vez diseñada la arquitectura del sistema que nos permite la adquisición de la RSSI de forma simultánea por las dos antenas en configuración monopolso, se realiza un amplio estudio teórico de la determinación del AoA en función del error de

cuantificación, de la variación con la distancia, del efecto multipath del suelo y del efecto multipath de las paredes.

Por último, se realiza otra contribución poniendo en marcha el sistema en un entorno real y demostrando que mediante la combinación de dos sistemas HAD es posible determinar con exactitud la posición (x,y) de un dispositivo IoT.

1.3.2 Caracterización de la Función monopulso en función de la distancia.

Las contribuciones de la aplicación de la función monopulso se ven ampliadas por la caracterización en función de la distancia de la misma y la determinación de un algoritmo que permite emplear una función monopulso diferente en función de la distancia hasta el dispositivo a localizar.

La contribución en este aspecto radica en la demostración de que la función monopulso varía con la distancia debido a las variaciones en los diagramas de radiación de las antenas. Por lo tanto, en el caso de no escoger la función monopulso apropiada, los errores angulares aumentan. Esta demostración se ha realizado de forma teórica, mediante experimentos en un entorno controlado como es la cámara anecoica y en un entorno real en el patio de la ETSIT.

1.3.3 Combinación de Función Monopulso y métrica RTT para generación de radar 2D

Otra contribución en el ámbito del uso de la función monopulso para la generación de sistemas de localización *indoor* ha sido la combinación de la función monopulso y de la métrica RTT para la implementación de un sistema de localización 2D empleando un único AP. Para llevar a cabo esta contribución, primero se diseñó el sistema empleando un AP comercial dotado de la métrica RTT que se equipó con antenas directivas de panel en configuración monopulso. El software de dicho AP fue modificado con el fin de obtener de forma simultánea la RSSI por las dos antenas junto con la RTT. Se posibilita así estimar el DoA y la distancia de forma simultánea. Mediante la combinación de las dos métricas se tiene un sistema preciso en 2D que permite obtener la posición (x,y) y requiere de solamente un AP.

Otra de las contribuciones dentro de este entorno fue la caracterización de la métrica RTT para comprobar que se debe de aplicar un offset que no varía en función de la distancia, sino que permanece fijo en 6000mm. Esta caracterización, realizada de nuevo tanto en entorno real como en cámara anecoica, demostró el mismo comportamiento con respecto al offset en los dos entornos.

Otra contribución dentro de este artículo son los resultados obtenidos del experimento realizado en un entorno real. Este experimento permitió evaluar la precisión de este tipo de sistemas frente a las tres variables fundamentales como son: la precisión con respecto al ranging empleando RTT, el error angular producido por la función monopulso, y el error con respecto a la posición (x,y) empleando la distancia Euclídea.

1.3.4 Uso de antenas frequency-beam y salto en frecuencia para la estimación del DoA

El dispositivo sniffer HAD empleado en los trabajos anteriores tiene el inconveniente de cubrir únicamente un FoV de 60°. Esto es debido al empleo de antenas directivas con un diagrama de radiación acotado. Entonces, al generar los diagramas suma, diferencia y computar la función monopulso, solo se obtienen valores unívocos en el rango de -30° a +30°. Con el fin de paliar esta limitación, se generó un nuevo *sniffer* que permite implementar el mecanismo de salto en frecuencia (*channel-hopping*). Además, las antenas de panel directivas empleadas en trabajos anteriores se sustituyen por antenas con haz de escaneo en frecuencia (*frequency-beam scanning antenna - FSA*). Mediante la combinación de estas dos componentes (*channel hopping* y *FSA*) y el uso del algoritmo MUSIC, se consigue ampliar el del sistema FoV a 180°. De nuevo, solamente se emplea información de la RSSI, evitando el empleo de información compleja de la señal.

Por último, las dos últimas contribuciones dentro de esta parte de la tesis son la realización de experimentos que permiten determinar el error angular obtenido por el sistema y la realización de una comparativa con el resto de sistemas de determinación de DoA que se pueden encontrar en la bibliografía.

1.3.5 Contribuciones a los sistemas de localización de smartphones mediante RSSI en grandes instalaciones

Las contribuciones en este ámbito vienen dadas por avances en varios ámbitos del desarrollo de sistemas de posicionamiento indoor de smartphones como son: i) generación y evaluación de toda una serie de herramientas empleadas en la generación de IPS (Indoor Positioning System); ii) evaluación de diferentes algoritmos de localización que permiten detectar el que tiene una mayor precisión; y iii) implementación completa de un sistema de marketing contextual empleando IPS.

Con respecto a las herramientas empleadas para la generación de IPS, se han procedimentado todos los pasos y se han generado las herramientas necesarias para implementar y desplegar un IPS en un entorno real, como puede ser un centro

comercial. Estas herramientas generadas y los procesos definidos cubren desde la creación del mapa digital hasta la validación del sistema generado.

En cuanto a la evaluación de diferentes algoritmos de localización *indoor*, se ha testado *Freeloc*, SVM y KNN en dos centros comerciales, empleando hasta 10 teléfonos diferentes y durante varias semanas. Los algoritmos se han testado con respecto a la evolución en el tiempo, la heterogeneidad del hardware y la afección producida por el fading. Estos algoritmos evaluados son la base para la generación de un IPS como el descrito en el párrafo anterior.

Por último, se ha definido y detallado todas las herramientas que se necesitan para la creación de un sistema de marketing contextual que permite interactuar con los visitantes de una gran instalación, siendo el IPS uno de los módulos fundamentales del sistema.

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Capítulo 2

Artículos publicados

Artículo 1

A Hybrid Analog-Digital Processing System for Amplitude-Monopulse RSSI-Based MiMo WiFi Direction-of-Arrival Estimation

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Hybrid Analog-Digital Processing System for Amplitude-Monopulse RSSI-based MiMo WiFi Direction-of-Arrival Estimation

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Abstract—We present a cost-effective hybrid analog digital system to estimate the Direction of Arrival (DoA) of WiFi signals. The processing in the analog domain is based on simple well-known RADAR amplitude monopulse antenna techniques. Then, using the RSSI (Received Signal Strength Indicator) delivered by commercial MiMo WiFi cards, the DoA is estimated using the so-called digital monopulse function. Due to the hybrid analog digital architecture, the digital processing is extremely simple, so that DoA estimation is performed without using IQ data from specific hardware. The simplicity and robustness of the proposed hybrid analog digital MiMo architecture is demonstrated for the ISM 2.45GHz WiFi band. Also, the limitations with respect to multipath effects are studied in detail. As a proof of concept, an array of two MiMo WiFi DoA monopulse readers are distributed to localize the two-dimensional position of WiFi devices. This cost-effective hybrid solution can be applied to all WiFi standards and other IoT narrowband radio protocols, such as Bluetooth Low Energy or Zigbee.

Index Terms—Direction of Arrival, Monopulse Antenna, RSSI-based localization, hybrid analog digital signal processing, MiMo.

I. INTRODUCTION

LOCALIZATION of mobile devices is a key enabling technology for emerging location-based applications [1], [2], cognitive radio systems [3], the Internet of Things (IoT) [4], or for future 5G systems [5]. Wireless positioning systems are based on measuring properties of the received RF signal. Basically there are three classes of RF signal quantities which are useful for a location algorithm: Direction of Arrival (DoA), Time of Arrival (ToA), and Received Signal Strength Indicator (RSSI) [6], [7]. Nowadays most of the proposed location systems with commercial hardware are based on the RSSI measurements using fingerprint techniques [8]–[11]. Acquisition and digital signal processing (DSP) of RSSI data is a cost-effective solution in commodity narrowband communication standards such as WiFi, Bluetooth Low Energy (BLE), or Zigbee. On the contrary, ToA requires accurate timing synchronization which is not possible with commodity and low-cost hardware.

Fig. 1. Two topologies of distributed network of directive antennas for RSSI localization a) Fingerprinting technique b) HAD monopulse readers.

On the other hand, DoA estimation approaches are based on arrays of antennas distributed in the localization area as sketched in Fig.1a [12], [13]. More complex antennas technologies, such as switched beam antennas or ESPAR (Electronically Steerable Passive Array Radiators), are often combined with complex signal processing algorithms like the well-known MUSIC [14], [15] or ESPRIT [16]. These processing techniques require specific hardware to get the amplitude and phase IQ data from the RF signals, and this is not available on commodity hardware, thus becoming expensive ad-hoc solutions.

In this paper we explore a low-cost and efficient system for DoA estimation of WiFi mobile terminals based on RSSI, using a simple hybrid analog-digital (HAD) architecture. The analog signal processing (ASP) at RF frequencies is performed by pairs of tilted directive antennas following well-known amplitude-monopulse RADAR techniques [17], [18], which are recently being proposed also for localization low-cost architectures [19]–[21]. Also recent is the concept of MiMo monopulse radar [22]–[24], in which a large amount of distributed monopulse antennas can be deployed as illustrated in Fig.1b. To avoid expensive dedicated hardware which performs the monopulse comparison in the RF analog signal processing (ASP) [17]–[20], and also expensive high-performance DSP circuitry to process IQ data [25], we propose non-coherent MiMo signal processing [26] in the digital domain using the RSSI baseband data obtained from commodity MiMo WiFi hardware.

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The proposed MiMo WiFi hybrid analog digital (HAD) RSSI-based monopulse DoA architecture is novel, and its presents two important features: a) its simple and low digital signal processing (DSP) computational cost since only RSSI data is needed (no IQ data), b) its robustness with respect to RSSI variations under certain conditions. As it is well-known, the use of RSSI in fingerprint-based localization schemes [8]-[11] suffer from RSSI variations due to the complex channel conditions (multipath and fading, mobility, temperature and humidity variations, inhomogeneous hardware, the relative orientation and height of the device [27]-[30]). As it will be shown, the proposed amplitude-monopulse DoA estimation technique absorbs some of the variations of RSSI, while reducing the complexity if compared to coherent DoA estimation which requires IQ data from specific hardware.

The paper is divided as follows. Section II presents the parts of the proposed MiMo WiFi HAD monopulse DoA system architecture: Section II.A describes the amplitude-monopulse antenna which performs the 2.45GHz RF analog signal processing, while Section II.B describes the analog-to-digital transformation to derive the digital MiMo WiFi monopulse DoA functions. Section III summarizes the overall hybrid AD DoA estimation performance. Special emphasis is given to the robustness and computation simplicity of this architecture if compared to other WiFi RSSI localization techniques. Finally, Section IV presents experimental results demonstrating the capability to estimate the 2D position of a user carrying a WiFi smartphone, to finalize the paper with the Conclusion Section.

Fig. 2. Scheme of the MiMo WiFi monopulse DoA system, illustrating the ASP (Analog Signal Processing) at 2.45GHz and the DSP (Digital Signal Processing) using RSSI data collected from commercial MiMo WiFi card.

II. HYBRID ANALOG DIGITAL SIGNAL PROCESSING FOR DOA

The general scheme of the proposed hybrid analog digital (HAD) architecture to estimate the Direction of Arrival (DoA) of WiFi signals is illustrated in Fig.2. The basic operations at the Reader are as follows: two commercial WiFi panel directive antennas [31] are arranged to permit monopulse analog signal processing (ASP) at RF 2.4GHz ISM band, as it will be described in detail in the next subsection II.A. A commercial 2X2 MiMo WiFi card based on Atheros AR9380 chipset [32] receives the WiFi frames signals from the monopulse antenna

array and sends this raw data to an embedded Linux PC. Then the WiFi MiMo monopulse reader sends the raw data to a server by means of an Ethernet wired connection, as shown in Fig.2. Finally, the server performs the monopulse digital signal processing which will be described in subsection II.B.

A. Analog RF amplitude monopulse signal processing

The measured 2.45GHz gain pattern of the commercial panel directive antennas [31] is plotted in Fig.3a for the horizontal H-plane (XZ plane), and in Fig.3b for the vertical E-plane (YZ plane). The angle is measured with respect to the perpendicular direction of the antenna (z-axis in Fig.3). As it can be seen, this antenna provides 14 dBi gain with linearly polarized radiation (in our case vertically polarized as sketched in the inset of Fig.3). Since the maximum cross-pol level is at least 15dB below the co-pol component, only this main polarization component will be considered in the following results. The directive antenna presents a half-power beam width $\theta_{HPBW}=30^\circ$ in both horizontal and vertical planes.

Fig. 3. Gain pattern for commercial WiFi panel antenna at 2.45GHz a) Horizontal plane b) Vertical plane. Angle θ is defined w.r.t. the z-axis.

Two panel antennas are mounted in a tripod and arranged in the x-direction side by side with a tilting angle $\alpha=7^\circ$ as shown in the inset of Fig.4. As it will be shown, this mechanical tilting must provide two mirrored radiation patterns which point to angles between one half and one third of the beam width θ_{HPBW} for an optimum monopulse response [18]. Antenna 1 is the one facing to positive azimuthal angles θ w.r.t. the z-axis (left side in Fig.4). The gain diagrams in the horizontal XZ plane were measured for each antenna in an anechoic chamber, and they are plotted in rectangular coordinates w.r.t. the horizontal angle θ . Antenna 2 showed a lower gain (11.8 dBi) than antenna 1: this 2.4 dB gain drop is attributed to losses in the connectors. In any case, due to the geometrical tilting, the main beam of each antenna is pointing to an angle of approximately $\pm 13^\circ$. This angle differs from the geometrical leaning angle $\alpha=7^\circ$ due to diffraction and coupling effects in the monopulse-array system. The array half-power beam widths have also slightly varied if compared to the single antenna (to $\theta_{HPBW}=33^\circ$) due to the array effects. Theoretical radiation patterns of ideal antennas with similar gains (14.2 dBi), beamwidths (33°), and scanning angles ($\pm 13^\circ$) are also plotted with dashed lines in Fig.4.

Fig. 4. Gain pattern at 2.45GHz in the horizontal plane for monopulse-array antenna system with $\alpha=7^\circ$.

This monopulse tilted-array configuration is commonly used in RADAR systems [18]. Simple analog-signal processing (ASP) is performed using the incoming RF signals amplitudes detected at each antenna. The following analog amplitude-monopulse function is defined:

$$\Psi_{RF}(\theta) = \frac{\Delta_{RF}(\theta)}{\Sigma_{RF}(\theta)} = \frac{P_{RF1}(\theta) - K_{RF} \cdot P_{RF2}(\theta)}{P_{RF1}(\theta) + K_{RF} \cdot P_{RF2}(\theta)} \quad (1)$$

where P_{RF1} and P_{RF2} are the power amplitudes—in linear form—of the RF signals received, respectively, at antenna 1 and 2 of the monopulse array. These are functions of the gain pattern of each antenna, and thus they depend on the azimuthal angle θ . Particularly, if the gain patterns of both antennas are symmetrical w.r.t. the perpendicular direction of the array $\theta=0^\circ$, similar RF power should be received at both antennas and the monopulse error should equal zero for a signal arriving from this perpendicular angle. However, asymmetries in the antennas gain patterns as the ones shown in Fig.4, introduce unbalance in the monopulse function. To correct for this unbalance, a compensating factor K_{RF} can be estimated from this difference in the received power at $\theta=0^\circ$:

$$K_{RF} = \frac{P_{RF1}(\theta=0^\circ)}{P_{RF2}(\theta=0^\circ)} \rightarrow K_{RF}(dB) = P_{RF1}(0^\circ) - P_{RF2}(0^\circ) \text{ (dB)} \quad (2)$$

From the measured gain patterns in Fig.4, a calibration value of $K_{RF}=2.4\text{dB}$ is obtained. Using this value in linear form ($K_{RF}=1.74$), the corrected power at antenna 2 ($K_{RF} \cdot P_{RF2}$) from the perpendicular direction $\theta=0^\circ$ equals the one received by antenna 1 (as can be seen by the red continuous line in Fig.4).

Fig. 5. Theoretical and measured analog amplitude-monopulse error functions

The corresponding analog amplitude-monopulse function (1) obtained from the measured and corrected gain patterns is shown in Fig.5. Also in this figure, the theoretical monopulse function obtained from the ideal gain patterns in Fig.4 is plotted. Good agreement is observed between theory and experiments in the analog RF domain. The Field of View (FoV) is determined by the angular region without ambiguity, so that the monopulse function presents a monotonous, quasi-linear variation from -1 to +1. It must be noticed that to obtain a proper FoV to estimate the DoA from the monopulse analog RF signal processing, the antennas radiation main beam widths and tilting angles must be properly chosen [17]. In our case, we obtain a FoV covering the angles from $\theta=-30^\circ$ to $\theta=+30^\circ$. Within this range, one can estimate the DoA of an incoming signal by analog processing of the RF powers measured at each antenna of the monopulse array. First, the analog amplitude-monopulse error function $\Psi_{RF}(\theta)$ (1) has to be estimated for all possible angles θ inside the FoV. Then, for a given received RF signal, the DoA is estimated by simple comparison with $\Psi(\theta)$.

B. Digital RSSI MiMo WiFi signal processing

The objective of the proposed system is to estimate the DoA of WiFi signals transmitted from mobile devices. The angular direction is measured w.r.t. the monopulse-array plane (in our case, the horizontal plane). For this purpose, the amplitude-monopulse ASP described in the previous section, has to be extended to the reception of 2.45GHz WiFi digital frames.

Fig. 6. a) MiMo WiFi card on embedded PC b) Monopulse MiMo WiFi reader.

As depicted in Fig.2, the mobile device (in our prototype a smartphone) is linked to a WiFi router which is transmitting WiFi frames on a regular basis. Every time the smartphone sends a WiFi frame, the reader sniffs the transmission. In more detail, the reader has a commercial MiMo 3X3 WiFi card based on AR9380 Atheros chipset [32], which is mounted on an embedded PC running Linux as illustrated in Fig.6a. This MiMo WiFi card allows connection to three different RF channels: two of them will be connected to the two antennas of the monopulse-array antenna, while the third one is matched to a 50Ω load. A sniffer program running on the embedded PC, collects the raw data from the received WiFi frames and build the raw data vector with the time stamp, reader ID, the smartphone's MAC address, and the Received Signal Strength Indicators (RSSI) measured at antenna 1 and antenna 2. This raw data is sent to the server by means of an UDP message using an Ethernet wired connection as illustrated in Fig.2.

Fig. 7. Experimental characterization of the correspondence between digital power indicator RSSI and real analog RF power a) Scheme of the experimental set-up b) P_{RF} -to-RSSI plot for the two channels of the MiMo WiFi card.

The RSSI is used in many WLAN localization systems [8], [10], [11]. In our case, we want to use the RSSI as a digital estimator of the real (analog) physical RF power P_{RF} received at each antenna, assuming a linear correspondence of the form:

$$RSSI_i(\theta) = \xi \cdot P_{RFi}(\theta) \quad i=1,2 \quad (3)$$

To check the assumption in (3), a complete characterization of the correspondence between the analog RF power and the RSSI values given by the WiFi MiMo card has been performed using the test set-up sketched in Fig.7a. A WiFi router is configured to send beacon frames using IEEE 802.11g standard [33] in channel #6 frequency (2.437 GHz) with a transmitted power of 17mW and a channel bandwidth of 20MHz. The RF SMA output of the WiFi router is connected with a RF coaxial cable to a set of cascaded RF attenuators, which can provide power attenuation at a physical (analog) level ranging from 10dB to 70dB attenuation. Then, a RF 1:2 splitter T-junction is used to divide the signal in equal outputs: one is connected to a Spectrum Analyzer [34] and the other output is connected to one channel of our 2X2 MiMo WiFi reader operating in sniffer mode. The analog RF power is measured from the Spectrum Analyzer integrating the received power spectrum density with a spectral mask of 22MHz (clause 17 from [34]). Then, this power is compared with the RSSI value obtained from the WiFi MiMo reader data, obtaining the plots shown in Fig.7b for both channels of the WiFi MiMo card. All this experimental setup is controlled by a PC running Linux connected via Ethernet cable to the different test modules (see Fig.7a). By interchanging a different amount of RF attenuators, a 60dB dynamic range in the received signal power is analyzed, as shown in Fig.7b. Also in this figure, the ideal $RSSI = P_{RF}$ function is represented in dashed line. Although there is not a 1:1 correspondence between the measured analog RF power and the digital RSSI

power read by the reader, what it is important is to observe that the assumed linear dependence (3) between analog and digital figures of power is checked, and with similar slopes. However, it can be observed that the $RSSI_1$ obtained at channel#1 is 3dB above the $RSSI_2$ read at channel#2 for similar analog RF powers. Moreover, this approximate 3dB difference between the two RSSI depends on the received power, as shown in Fig.7b. Therefore, this offset is power dependent and this has to be considered in the digital signal processing of the monopulse DoA system, as it will be shown.

The RSSI angular patterns measured in an anechoic chamber are shown in Fig.8a. A smartphone transmits WiFi signals, which are received by our MiMo WiFi monopulse reader. Received WiFi frames are filtered so that only those with MAC address of the smartphone under test are processed. The $RSSI_i$ at each antenna channel ($i=1,2$) is measured as the relative line-of-sight (LoS) azimuthal angle θ is swept from -90° to $+90^\circ$. As expected, the RSSI level received at each antenna follows the corresponding monopulse-array angular radiation patterns, which agree very well with the analog ones as compared in Fig.8b. Besides, the $RSSI_2$ signal presents a lower level than $RSSI_1$, which can be corrected applying a digital compensating factor K_D as illustrated in Fig.8a.

Fig. 8. a) Measured digital power (RSSI) angular patterns at the MiMo WiFi monopulse reader b) Comparison between digital (RSSI) and analog (RF power) monopulse-array normalized radiation patterns.

As done in the analog domain case, the digital correction coefficient K_D is extracted from measured $RSSI_i$ levels at the perpendicular direction $\theta=0^\circ$:

$$K_D = \frac{RSSI_1(\theta=0^\circ)}{RSSI_2(\theta=0^\circ)} \rightarrow K_D(dB) = RSSI_1(0^\circ) - RSSI_2(0^\circ) \quad (4)$$

This digital correction must be performed for power values in a specific operating power range, since as previously

commented the power characterization shown in Fig.7b is slightly power-dependent. For that, K_D is computed by moving along the perpendicular direction in a range of distances inside the localization zone –in our case from 1 to 15 meters far from the reader-. Then, we obtain an averaged digital correction value of $K_D=4\text{dB}$ ($K_D=2.51$ in linear form). This is coherent with the summation of the afore-mentioned unbalancing effects ($K_{RF}=2.4\text{dB}$ due to asymmetries in analog-domain monopulse-array RF radiation patterns –see Fig.4, plus 2dB due to unbalance in the MiMo WiFi RSSI digital channels, see Fig.7b).

Fig. 9. Digital amplitude-monopulse function compared to its analog counterpart.

Once K_D is obtained, a digital amplitude-monopulse function can be defined from the relative RSSI values at different angles:

$$\Psi_D(\theta) = \frac{\Delta_D(\theta)}{\Sigma_D(\theta)} = \frac{RSSI_1(\theta) - K_D \cdot RSSI_2(\theta)}{RSSI_1(\theta) + K_D \cdot RSSI_2(\theta)} \quad (5)$$

This digital function is plotted in Fig.9 and it is compared with analog (1) and theoretical monopulse functions, observing good agreement. A reduced FoV of $[-30^\circ, +20^\circ]$ is obtained in the digital domain. The performance of the proposed MiMo WiFi HAD monopulse architecture to estimate the DoA is studied in the next Section.

III. DOA PERFORMANCE

Very simple digital signal processing is applied to estimate the DoA. Once the digital monopulse system has been calibrated by obtaining K_D (4), the amplitude-monopulse value from the received digital RSSI_i data is directly computed as:

$$\Psi_{RSSI} = \frac{\Delta_{RSSI}}{\Sigma_{RSSI}} = \frac{RSSI_1 - K_D \cdot RSSI_2}{RSSI_1 + K_D \cdot RSSI_2} \quad (6)$$

Then, a simple numerical search is performed to obtain the estimated angle θ_{EST} which minimizes the following monopulse comparison error function:

$$\theta = \theta_{EST} \xrightarrow{\text{yields}} \min |\Psi_D(\theta_{EST}) - \Psi_{RSSI}| \quad (7)$$

It must be noticed that this digital RSSI-based DoA estimation algorithm can be performed in real time and simultaneously for multitude of WiFi mobile terminals (each one with its corresponding filtered MAC address). This multi-user real-time capacity is possible to the reduced computational effort, since part of the signal processing is implemented in the analog domain by the RF monopulse antenna array.

The DoA estimation performance of the proposed WiFi MiMo HAD monopulse system, is studied in the following subsections with respect to different situations.

A. Quantization Error

The RSSI values obtained from the MiMo WiFi card are quantized in 1dB steps [32]. Therefore, the digital amplitude-monopulse function $\Psi_D(\theta)$ is also a discretized function with a minimum step, which can be computed from the case in which the RSSI in one of the channels (for instance #1) varies in 1 dB:

$$RSSI'_1(\text{dBm}) = RSSI_1(\text{dBm}) + 1\text{dB} \rightarrow RSSI'_1 = 10^{0.1} RSSI_1 \quad (8)$$

and also considering that the linear values of RSSI at each channel (after compensating channel #2 with K_D) can be related with a proportion constant χ which depends on the angle θ :

$$RSSI_1 = \chi(\theta) \cdot K_D \cdot RSSI_2 \quad (9)$$

Fig. 10. Effect of the RSSI quantization in the DoA estimation error.

Obviously, $\chi(\theta)$ depends on the monopulse system digital angular pattern shown in Fig.8a, obtaining the function $\chi(\theta)$ in logarithmic and linear scales shown in Fig.10, for the angular range inside the FoV $\theta = [-30^\circ, +20^\circ]$. As it can be seen, $\chi=1$ for $\theta=0^\circ$, since both digital channels provide similar corrected RSSI values. At the FoV sides, $\chi \approx 10$ for $\theta=+20^\circ$, since RSSI₁ is 10 dB above RSSI₂ due to the 10dB difference of the monopulse antenna radiation patterns (see Fig.8a), and conversely $\chi \approx 0.1$ for $\theta=-20^\circ$ since in this case RSSI₁ is 10 dB below RSSI₂. Introducing (8) and (9) in (6), the quantization error $\delta\Psi_D$, can be computed as a function of $\chi(\theta)$:

$$\delta\Psi_D(\theta) = \frac{2 \cdot \chi(\theta) \cdot (10^{0.1} - 1)}{(\chi(\theta) + 1) \cdot (\chi(\theta) + 10^{0.1})} \quad (10)$$

obtaining the result plotted in Fig.10. As shown, this quantization error is larger for perpendicular angles than for angles at the FoV sides due to the difference between the associated RSSI levels. As a result of this error $\delta\Psi_D$, the DoA angle estimated using (7) suffers an error $\delta\theta$ which again is larger for angles in the perpendicular direction than on the edges. As shown in Fig.10, $\delta\theta \approx 2.5^\circ$ for $\theta=0^\circ$, while for $\delta\theta \approx 1^\circ$ for $\theta=\pm 20^\circ$. The digital quantization of the RSSI therefore limits

the highest theoretical resolution of this HAD monopulse DoA system to this scale. The quantized digital monopulse function showing this dependence in the angular resolution with respect to the DoA is illustrated in Fig.11.

Fig. 11. Effect of the RSSI quantization in the DoA estimation error.

B. Range Variations

One of the main features of monopulse-based DoA systems is the associated robustness with respect to absolute amplitude deviations which affect both monopulse channels with the same variation level. In other words, since the monopulse function depends on the *relative* power values received between the two channels, any amplitude variation which simultaneously affects the two antennas in the same manner, will not affect the overall monopulse function. Therefore, the estimated DoA will not be affected by any signal strength variation which is sensed equally in the two channels. This is a key advantage if compared to other RSSI-based localization architectures which depend on the absolute values of RSSI [8]-[11], and which can be strongly affected by received power variations due to obstacles, orientation of the mobile device, temperature and/or humidity changes... etc [27]-[30]. Obviously, electronic noise which is uncorrelated in each reception channel cannot be absorbed by the monopulse system, and will introduce uncertainty / noise in the estimated DoA as it will be shown.

Fig. 12. Variation of the received digital power as a function of the distance and for different angular directions.

To illustrate this robustness of the estimated DoA w.r.t. absolute variations in the received power, Fig.12 shows the theoretical and measured variations for the RSSI at each

channel of the MiMo WiFi monopulse reader, as a function of the distance. The experiments are performed in an anechoic chamber to minimize multipath effects, and for different line-of-sight (LOS) angular directions w.r.t. the monopulse reader, θ_{LOS} . The maximum distance was limited to 3 meters due to the anechoic chamber size. For the perpendicular direction $\theta_{LOS}=0^\circ$, similar values of RSSI₁ are received at both channels for any distance, even if the absolute values decrease with distance as predicted by theory. As a result of this similar relative values of RSSI, the theoretical amplitude monopulse value (6) should be $\Psi_{RSSI}=0$, leading to an estimated DoA (7) $\theta_{EST}=0^\circ$. However, due to system noise the monopulse function varies as can be seen in Fig.13, producing an error in the estimated DoA of $\pm 5^\circ$. This error increases close to the reader, where the far-field tilted antenna radiation patterns used to estimate the digital monopulse function are not valid anymore.

Fig. 13. Variation of the digital monopulse function and the estimated DoA as a function of the distance and for different angular directions.

For other angular directions, the expected difference in the relative RSSI levels due to monopulse angular patterns is obtained. For instance for $\theta_{LOS}=+20^\circ$, RSSI₁ is 10dB higher than RSSI₂ as shown in Fig.12. Moreover, this relative difference keeps almost constant for any distance, and thus the associated monopulse function value is stable around $\Psi_{RSSI}=0.8$ making the estimated DoA robust w.r.t. range distance variations as shown in Fig.13. Again, fluctuations are observed due to noise overlapped to quantized RSSI values, observing that this quantization error is higher for $\theta_{LOS}=0^\circ$ than for $\theta_{LOS}=+20^\circ$ as explained in the previous section. Similar results are obtained for $\theta_{LOS}=-20^\circ$, where RSSI₁ is 10dB lower than RSSI₂ for any range distance as shown in Fig.12.

C. Effect of Multipath Due to Floor

In a real scenario, multipath due to surrounding obstacles must be considered. To model the effect of reflection with floor, the setup illustrated in Fig.14 has been experimentally and theoretically analyzed. A metallic sheet has been placed on the floor of the anechoic chamber, and the distance of the WiFi mobile terminal to the reader has been varied.

Fig. 14. Scheme of monopulse antenna array system with floor reflections.

A simple direct plus reflected ray-tracing approximation has been used to model the power received by each antenna of the monopulse array. For a given LoS direction θ_{LOS} and for any distance R between the smartphone and the center of the MiMo WiFi reader, the theoretical power received at each antenna can be computed as:

$$E_{RFI}(R) = g_i(\theta_H, \theta_V) e^{-jk d_{Ai}} \left[\frac{1}{d_{Ai}} + \frac{\rho \Delta g_{Ri}}{d_{Ai} + \Delta d_{Ri}} e^{+j(\varphi_{gRi} - k \Delta d_{Ri})} \right] \quad (11)$$

$$P_{RFI}(R) = |E_{RFI}(R)|^2 \quad (12)$$

where ρ is the reflection coefficient of the floor (in our case a metallic floor $\rho=1$ which is the worst case scenario), k is the free-space wavenumber at 2.45GHz, and $g_i(\theta_H, \theta_V)$ is the gain pattern of antenna $i=1,2$, as a function of the horizontal plane angle θ_H and the vertical plane angle θ_V . Eq.(11) includes the phase and amplitude differences of the two waves interfering at each antenna, namely the direct and the reflected waves. More particularly, the direct wave travels a distance d_{Ai} to each antenna, while the reflected wave propagates through an extra path given by Δd_{Ri} , which is computed by simple trigonometry for each antenna and for any position R and any LoS direction θ_{LOS} , taking into account the height of the reader H_S and the height of the mobile H_M (see Fig.14). Also in (11), it is considered that both waves are received at each antenna with different complex gains (amplitude and phase) due to the unequal elevation angles from which they enter the antenna. As shown in Fig.14, the direct wave enters perpendicular to the antenna elevation plane, while the reflected wave enters by an elevation angle which depends on the reflection angle θ_{VR} . This effect is modeled in (11) with an amplitude and phase difference given, respectively, by Δg_{Ri} and φ_{gRi} . Finally, it must be noticed that the distance S between the two antennas to the center of the array in the x -direction, has also been considered to compute the path lengths for each ray (see Fig.14).

Fig. 15. Variation of RSSI, digital monopulse function and estimated DoA as a function of the distance in the presence of reflective floor for $\theta_{LOS} = -15^\circ$.

In our setup, $S=26\text{cm}$ and $H_S=H_M=1.5\text{m}$. From the complex field due to the interference between the direct and reflected wave field (11), the power at each antenna is computed by (12). Results are plotted in Fig.15 as a function of the mobile-reader distance R from 1.5m to 3m, and for a constant horizontal angle $\theta_{LOS} = -15^\circ$. Measured digital RSSI levels are consistent with theoretical results.

As it can be seen, the received powers at each antenna follow a typical interference pattern, showing quasi-oscillatory behavior superposed to the monotonous decay with distance. The effect of multipath is evident if compared to Fig.12 where only direct wave was present. Most important is to understand that the monopulse system is very robust with respect to this multipath effect due to floor, since both reception channels suffer almost similar oscillatory variation. As a result, the data in the monopulse function keep almost constant as it can be seen in Fig.15. Eventually, the estimated DoA angle keeps quite stable with distance variations, showing a mean value around the real LoS angle of -15° .

D. Effect of Multipath due to Lateral Walls

Finally, the effect of multipath from lateral reflections is studied, following the scenario shown in Fig.16.

Fig. 16. Scheme of monopulse antenna array system with lateral reflections.

Fig. 17. Variation of RSSI, digital monopulse function and estimated DoA as a function of the distance in the presence of reflective floor for $\theta_{LOS} = -15^\circ$.

The key difference with respect to floor multipath, is that the interference patterns created at each monopulse channel are very distinct. Certainly, now the reflected wave produces unequal contribution for each antenna of the monopulse array. As an example, in the scheme of Fig.16, the reflected wave enters antenna #1 much more strongly than antenna #2 due to the tilted angular pattern of the monopulse array in the horizontal XZ plane. On the contrary, in the case of reflections in the floor in Fig.14, the reflected wave enters the monopulse array in a similar angle for both monopulse antennas since the multipath is produced in the vertical YZ plane and not in the horizontal ZX plane.

To illustrate this difference, Fig.17 shows the results for a similar LoS angle $\theta_{LOS} = -15^\circ$ and similar distance variation than in the previous subsection. A metallic lateral wall is located at a horizontal distance $X_W = 0.8m$ from the reader (see Fig.16). As can be seen, now the power received at each channel behaves in a very dissimilar manner. Oscillations due to constructive and destructive interferences appear as with floor multipath: however, these oscillations are no more coherent in both channels. As a result, the relative power levels strongly vary with distance, making the monopulse function and the associated estimation of the DoA to be very sensible to distance variations. As it can be seen, the DoA given by the monopulse system shows deviations from $\theta_{LOS} = -20^\circ$ to $\theta_{LOS} = +10^\circ$. Again, good agreement is observed between measured digital RSSI at each channel and simple interference theory.

Therefore, it can be concluded that the proposed MiMo WiFi HAD monopulse DoA estimation system is robust with respect to range variations if the effect of lateral obstacles is negligible. In a real indoor scenario, the monopulse technique can be combined with Neural Network post-processing in order to mitigate indoor multipath as proposed in [39].

IV. X,Y LOCALIZATION

Fig. 18. Scheme of two MiMo WiFi readers to estimate X,Y coordinates.

Several readers can be located at different locations to estimate their relative DoA, and from the distributed relative data deduce the absolute position in a two-dimensional X,Y grid. As sketched in Fig.18, a minimum of two readers are needed to obtain the 2D intersection between their corresponding lines, although normally more than two DoA estimators are used for a more robust 2D localization schemes [6],[7],[19]-[24]. This way, as the number directive antennas is increased, a distributed disperse array of antennas must be somehow deployed in the area, as it was shown in Fig.1. The collected RSSIs from all the readers are then processed by the server to estimate the positions of the mobile terminals using different algorithms, most of them, fully digital, based on RSSI fingerprints [8]-[11].

Fig. 19. Picture of two MiMo WiFi monopulse readers deployed in outdoors.

In our case, the monopulse antenna array from each reader defines a triangle by its respective orientation and Field of View (FoV). As illustrated in Fig.18 for the case of two readers, the shadowed intersection zone is the region where WiFi devices can be localized without ambiguity by using the proposed simple HAD monopulse technique. Fig.19 shows a picture of a real outdoor deployment of two monopulse readers in a rural area. The two readers are orthogonally (90°) located following the scheme in Fig.18, so that the center of the localization region defines the origin of the absolute X,Y coordinate system, which is at a distance of 8 meters from each reader.

Fig. 20. X,Y localization performance.

In the outdoor experiment, 15 test points were located at the intersections between the relative equiangular lines of $-20^\circ, -10^\circ, 0^\circ, +10^\circ, +20^\circ$ of the two monopulse readers. It must be observed that these test points are not symmetrically located w.r.t. the readers in Cartesian coordinates. For all these test points, the DoA estimated by each MiMo WiFi reader was computed in real time and processed by a local server, which ultimately predicted the estimated X,Y position. The results for the 15 test points at the intersections of the central lines ($\theta=0^\circ$) and edge lines ($\theta=\pm 20^\circ$) of the two readers FoVs are summarized in Fig.20. The test points are represented with circles, and the estimated positions with triangles. The mobiles positions are tracked in real time, with extreme simplicity and average accuracy of 1 meter, which is consistent with the reported 5deg DoA average accuracy and the distances in this experiment. Obviously, for a similar angular resolution, the X,Y localization error is higher as the distance to the DoA monopulse reader increases. As a result, the localization error is greater for the furthest test location (intersection between reader #1 $+20^\circ$ line and reader #2 -20° line, see Fig.20), where an error of 1.5 meters is obtained.

Finally, the robustness of this DoA estimation system with respect to the relative position of the WiFi device, is studied. For that purpose, the received RSSI signals are analyzed in a period of 40 seconds in which the device holder sequentially moves the smartphone among three different common uses: speaking, reading and smartphone hidden inside a trousers pocket. These three uses are coded as A, B and C, respectively, in the inset of Fig.21. As shown, the RSSI shows a 15dB drop when the mobile is inside the pocket, while slighter variations are observed between speaking and reading modes. Nevertheless, what is again important is to observe that the RSSI levels measured by the two channels of each monopulse array vary in the same manner, leading to almost null *relative (differential)* RSSI variation. As explained previously, this keeps the monopulse function almost unchanged despite this type of signal variations, and so does the estimated DoA, as it can be seen in the measured results in Fig.21.

Fig. 21. Variation of RSSI, monopulse function and estimated DoA as the smartphone is modified from speaking, reading and hidden-in-pocket modes.

Similar results are obtained when the relative orientation of the mobile terminal is modified, i.e., when the person changes facing forward, backward and lateral w.r.t the monopulse readers. Again, this robustness w.r.t mobile orientation changes is explained from the fact that these variations alter to the same extent the RSSI at both channels of each monopulse reader, thus keeping stable the estimated DoA. Similar stability with respect to humidity, temperature and other RF channel fluctuations is expected, thus being superior in this aspect than RSSI-fingerprint-based techniques [27]-[30].

Certainly, this robustness is achieved thanks to the use of analog RF monopulse techniques which gather each pair of antennas of the total distributed antenna network in a more efficient manner. As illustrated in Fig.1b and described in Section II.A, each pair of directive antennas must be arranged together and geometrically tilted to a given angle α (which depends on their directive beam half power beam-width θ_{HPBW}), so that their radiation patterns properly overlap and produce an adequate monopulse function with their respective FoV. As an example, Fig.22 illustrates the dependence of the analog RF monopulse function for directive antennas with $\theta_{HPBW}=35^\circ$ (similar to the ones used in this work), and for different geometrical leaning angles α (which turn into different angles of maximum radiation of their respective radiation patterns θ_M).

Fig. 22. Dependence of the analog RF monopulse function for two directive antennas with $\theta_{HPBW}=35^\circ$, and for different geometrical tilting angles.

Table I – Comparison between the proposed WiFi HAD monopulse DoA architecture and other WiFi localization metric alternatives.

REF	Architecture	Performance	Complexity
[8], [35]-[41]	Only RSSI-based fingerprinting system	Meters indoor	Medium. RSSI acquisition is simple. Exhaustive data acquisition training phase, and need of classification algorithms
[42],[43]	CSI-based phased-antenna techniques for DoA estimation	Centimeters indoor	High. Phase information (CSI) required. Hardware and software modifications for accurate phase-delay measurement.
[44]	CSI-based MUSIC algorithm for DoA and ToA estimation	Decimeters indoor	High. Phase information (CSI) required. MUSIC algorithm to estimate ToA and DoA.
[45],[46]	CFR-based fingerprinting system	Centimeters indoor	High. Channel Frequency Response (CFR) required. Exhaustive data acquisition training phase, and need of classification algorithms.
this paper	RSSI-based DoA estimation using monopulse technique	Decimeters outdoor	Low. RSSI acquisition is simple. No need of exhaustive data acquisition and training phase, only calibration of correction factor. No need of classification algorithms to estimate the DoA.

As it can be seen, the slope of the analog monopulse function can be engineered, so that higher values of α produce steeper angular monopulse responses (see blue dotted line in Fig.22). This reduces the FoV, but increase the angular resolution since the angular error due to digital quantization is reduced, as explained in Section III.A. Conversely, less tilted antennas (lower α) increase the FoV at the cost of higher angular error / less angular resolution, as shown in red dashed line in Fig.22.

V. COMPARISON WITH STATE-OF-THE-ART ALTERNATIVES

A concluding Table I compares the proposed HAD DoA architecture with other alternatives found in the literature, in terms of localization performance and simplicity. The RSSI metric has been extensively used for fingerprinting-based WiFi localization algorithms ([8], [35]-[41]). These RSSI-based fingerprinting techniques do not estimate the DoA of the signals. They only use the signal strengths to construct power-based RSSI radiomaps.

The combination of different metrics (RSSI, DoA and ToA) have demonstrated superior performance if compared to only-RSSI based fingerprinting localization systems. For this reason, the estimation of the DoA has been pursued in many WiFi localization architectures [42]-[46]. In this context, WiFi is not compatible with ultrawideband DoA techniques which require high-bandwidth (such as [47] and [48]), which is not available in WiFi technologies. To estimate the DoA in WiFi systems, previous proposals rely on phase-delay information which requires much more complex IQ hardware than solutions based only on RSSI (amplitude information). For instance, ArrayTrack [42] and Phaser [43] estimate the DoA using

phased-array antenna techniques based on CSI (Channel State Information) acquisition and processing. In the same manner, Spotfi [44] estimates the DoA and the ToA using CSI data and super-resolution MUSIC algorithms. In any case, CSI data is not available in commodity hardware, and hardware/software modifications are requested to solve the differences in phase of the oscillators for accurate phase-delay prediction. Therefore, these CSI-based DoA architectures [42]-[44] are more complex solutions than those based only on RSSI as the one proposed in this paper. Finally, other WiFi localization solutions are based on processing of the CFR (Channel Frequency Response) for multiple frequency channels [45], or for multiple antennas [46]. Again, the CFR acquisition relies on specific hardware and software. Also, to construct the CFR radiomap, an exhaustive data acquisition training phase is requested, and an algorithm is necessary to compensate residual synchronization errors.

For all these reasons, the RSSI-based DoA monopulse architecture proposed in this work is much simpler, since it relies on direct measurement of the RSSI, and it does not need extra training or calibration phase for precise IQ data processing. In our case, the simple estimation of the afore described correction factor is sufficient as demonstrated in this paper. However, this simplicity provides lower resolution (in the order of $\pm 2.5^\circ$) and lower robustness w.r.t. indoor multipath effects, than more complex DoA CSI/CFR-based techniques [42]-[46]. In future works, the monopulse technique will be combined with machine learning algorithms in order to mitigate indoor multipath as proposed in [39], [49], and envisage a complete WiFi indoor localization system based on this architecture fusion with fingerprinting techniques. Moreover, heterogeneous networks (WiFi plus cellular) information can be combined for enhanced positioning performance [50], [51].

VI. CONCLUSION

We have presented a cost-effective hybrid analog digital monopulse system where MiMo WiFi readers estimate the Direction of Arrival (DoA) of RF transmissions from smartphones. The reader has a commercial MiMo WiFi card with attached directive antennas in a tilted monopulse configuration. The processing in the analog domain is based on simple well-known RADAR amplitude monopulse antenna techniques. On the digital domain, the reader monitors the WiFi frames transmitted from each device and measures its RSSI (Received Signal Strength Indicator). Then, the DoA is estimated using the so-called digital monopulse function. Finally, as a proof-of-concept, two readers operating at 2.45GHz are distributed outdoors in order to localize the two-dimensional position of a person carrying a smartphone. In spite of using commodity hardware, we demonstrate that the DoA estimation is robust against the RSSI fluctuations produced by the smartphone orientation, floor multipath effects and range variations. Due to the hybrid analog digital architecture, the digital processing of the DoA is extremely simple with reduced computational cost and can enrich the widely proposed WiFi RSSI-based fingerprinting location systems. Currently, the proposed RSSI-based HAD monopulse architecture is being developed for tracking WiFi smartphones in open wide-area mass events, and also for IoT devices based on Bluetooth Low Energy and Zigbee.

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Artículo 2

Near-Field Monopulse DoA Estimation for Angle-Sensitive Proximity WiFi Readers

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Near-Field Monopulse DoA Estimation for Angle-Sensitive Proximity WiFi Readers

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ABSTRACT We study the effect of close-proximity in the estimation of the Direction-of-Arrival (DoA) using a monopulse antenna array system, with application to angle-sensitive proximity WiFi readers. It is shown that in this scenario, it is necessary to consider near-field radiative effects to make an accurate angular estimation at short distances between the mobile terminal and the DoA proximity sensor. As a result, we define a range-dependent angular monopulse function, which provides a better DoA estimation in a Field of View of 60° and for distances ranging from 3 m to 50 cm.

INDEX TERMS Direction-of-arrival, monopulse system, near-field region, proximity detection, WiFi.

I. INTRODUCTION

Proximity sensing of wireless mobile devices is a chief feature for many proximity-based services in the context of the Internet of Things (IoT) in Smart Cities. Among these applications, we can mention proximity-aware activation in smart buildings (such as interactive spaces) [1], machine-to-machine close-physical interaction without human intervention [2], and microlocation at indoor spaces [3]. Although BLE (Bluetooth Low Energy) has been considered as a promising wireless standard for such proximity-based applications due to its low-power, low-cost, low-connectivity range characteristics [4], [5], more recently the WiFi Alliance has defined a new low-power discovery over WiFi standard for proximity applications: the Neighbor Awareness Network also known as WiFi Aware [6]–[8].

Here proximity refers to the relative distance to an object (the sensor), and this should not be confused with indoor location which stands for the absolute position within a given environment. The sensor may be attached to moving objects, and the proximity information may trigger an event depending on the nearness, allowing seamless interaction between a user and the object. In this context, measuring not only the relative distance (ranging) but also the relative direc-

tion (angulation), provides richer information for proximity-based contextual services and machine-to-machine physical interaction.

Low-cost proximity ranging estimation with WiFi signals is typically performed from the RSSI (Received Signal Strength Indicator) which can be acquired from WiFi radios, and using indoor propagation models to relate the received power of RF signals to the relative distance between the transmitter and the receiver [9], [10]. ToF (Time-of-flight) based ranging methods [11] are more accurate but at a higher cost due to the need of synchronization (since the estimated distance results from the product of the packet propagation time and the speed of light).

On the other hand, relative angular estimation (also known as DoA, Direction of Arrival) between WiFi devices can be performed using two main signal-processing techniques: phase-based or power-based. As in ranging techniques, more accurate phase-based DoA techniques rely on more complex hardware and signal processing (involving IQ data and synchronization [12]), than power-based DoA techniques which can be applied directly to RSS data [13]. In any case, DoA estimation requires some type of smart antenna array which is capable to measure the inter-element phase or the relative power at different spatial directions [14], [15].

One type of antenna array especially suited for low-cost RSSI-based DoA estimation is the monopulse array, which

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FIGURE 1. Monopulse-array individual radiated field intensity distributions.

was originally applied for long-range RADAR systems [16]. It is basically formed by an array of two antennas producing two directive tilted reference radiation patterns (sketched in Fig.1), which are combined using a monopulse network to derive a sum (Σ) and a difference pattern (Δ). From the relative power levels of these two input channels (Δ / Σ), the DoA can be estimated with high angular resolution in a given Field of View (FoV). Narrower beams provide higher angular resolution but reduced FoV [16].

More recently, the monopulse array concept has been applied for DoA estimation in low-cost Wireless Networks and IoT-related applications, such as 900 MHz band RFID [17]–[20] and 2.45 GHz band WLANs [21]–[24]. In all these cases, the monopulse system provides angular information which cannot be obtained with single-element antennas, and which can be used to add sense of motion and directional information to the conventional proximity reader. Due to its simplicity, the monopulse system is also used in many educational laboratories to teach antenna systems, microwave engineering and signal processing [25]–[29].

In any case, the monopulse-array DoA sensor uses the far-field radiation patterns to characterize the monopulse angular function Δ/Σ , which univocally associates the relative RSS levels to a DoA within the FoV. Still, the far-field assumption might not be accurate for proximity angular sensors, and this could lead to inaccurate DoA estimation. In this work we analyze the near-field effects for a practical monopulse-array sensor designed for WiFi devices in the 2.45 GHz band [24]. Section II describes the theoretical background, showing the near-field effects which appear for distances below 3 meters, and their implications in the monopulse-array technique for DoA estimation. In Section III, a range-dependent near-field monopulse function is defined, which takes into account these effects and provide more accurate DoA predictions at short distances. Finally, Section IV reports experimental validation.

II. THEORETICAL BACKGROUND

A monopulse array synthesizes two partially-overlapped tilted directive radiation patterns, so that any incoming RF signal will create two independent power measurements Δ and Σ , whose relative levels can be univocally related to the angle of DoA. As an example, Fig.1 plots the theoretical radiated-field intensity at 2.45 GHz in the region surrounding the monopulse reader proposed in [24]. It is formed by two commercial WiFi panel antennas (with size 20cm $\times$ 20cm, 14 dBi peak gain and 30° HPBW -Half Power Beam Width- [30]) which are tilted $\pm 7^\circ$ to create the desired partial overlapping.

The fields radiated by antenna 1 (tilt $+7^\circ$) are plotted with blue contours in Fig.1, while the fields of antenna 2 (tilt -7°) are plotted with red contours. As it can be seen, the fields radiated by each individual antenna create two well-defined directive beams tilted at $\pm 7^\circ$ to create the desired partial overlapping. It must be remarked that the radiation patterns considered for the design of monopulse systems are usually defined in the far-field regime [16]. It is well-known from antenna theory, that the zone surrounding any antenna can be divided in three distinct regions called the Rayleigh or reactive near-field region (with dominant reactive components of electromagnetic fields), the Fresnel or radiative near-field region (where radiated near fields are dominant but the far-field pattern is not formed yet), and the Fraunhofer or far-field region (where the radiation pattern has a stable angular shape which does not depend on radial distance) [31]. These three zones are delimited by the following expressions:

$$d_{\text{NEARFIELDS}} = 0.62 \cdot \sqrt{\frac{S^3}{\lambda}} \quad (1)$$

$$d_{\text{FARFIELDS}} = 2 \cdot \frac{S^2}{\lambda} \quad (2)$$

where S stands for the maximum size of the antenna array and λ is the wavelength. In our case with $S = 45$ cm and $\lambda = 12.24$ cm we obtain a far-field limit of 3.3 m and a near-field limit of 53 cm. Therefore, for proximity sensing applications our monopulse array will operate in the Fresnel zone for distances below 3 meters. As it can be seen in the simulated angular patterns plotted in Fig.2, effectively the directive beams of the monopulse array show a stable angular shape for distances above 3 meters. However, as we get in closer proximity to the antenna array, the beams start to distort from their far-field forms. To quantify this effect, the theoretical angle of maximum field intensity is plotted against distance in Fig. 3, showing that only in the Fraunhofer region ($r > 3.3$ m) the beams pointing angle becomes independent on the distance and equal to the designed tilted angle of 7° using far-field theory. In the Fresnel region, the radiated beams direction squints to higher angles, reaching values above 15° in the 50 cm to 1 m range.

Obviously, these near-field beam distortions will impact the monopulse system performance if they are not considered. To evaluate the theoretical effects, the monopulse function

FIGURE 2. Monopulse-array individual field intensity patterns as a function of distance.

FIGURE 3. Evolution of the peak direction for the monopulse beams in Fig.2 as a function of distance.

(defined as the ratio between the difference Δ and the sum Σ patterns as a function of angle θ), can be analyzed as a function of the radial distance r :

$$\Psi(\theta, r) = \frac{\Delta(\theta, r)}{\Sigma(\theta, r)} \quad (3)$$

Theoretical spatial distributions of the monopulse sum and difference fields in a region close to the monopulse array are plotted in Fig.4. The angular cuts at different radial distances r are shown in Fig.5, where the patterns have been normalized to better compare the relative distortion of their angular shapes as we get in closer proximity to the antenna array.

Effectively, the monopulse patterns become stable only for distances larger than 2 meters. At one-meter distance, the sum pattern Σ starts broadening and the two lobes of the difference pattern Δ start to separate. At 50 cm, the distortion is more pronounced, and the Σ lobe shows a dip at the perpendicular direction ($\theta = 0^\circ$), while the Δ lobes continue splitting away to further directions. At 25 cm, the individual beams totally split away and they do practically not overlap (see Fig.2), and this translates into almost undistinguishable

FIGURE 4. Monopulse-array sum (Σ) and difference (Δ) radiated field intensity distributions in the vicinity of the monopulse array.

FIGURE 5. Normalized monopulse-array sum (Σ) and difference (Δ) patterns as a function of radial distance.

Σ and Δ patterns but in a narrow angular region around the perpendicular direction.

The resulting angular monopulse function (3) for different radial distances r is plotted in Fig.6. The far-field monopulse function for distances $r > 3$ m shows a Field of View without ambiguity (where there is a unique correspondence between the monopulse function and the DoA) of $\pm 30^\circ$. For $r = 1$ m the near-field monopulse function distorts to a more compressed shape, thus resulting in a lower FoV of $\pm 25^\circ$. This effect becomes more remarkable for $r = 50$ cm showing a FoV below $\pm 20^\circ$. The FoV eventually reduces to very limited angular range of $\pm 10^\circ$ for a close distance $r = 25$ cm, where

FIGURE 6. Monopulse function (Δ/Σ) at different radial distances.

FIGURE 7. Monopulse ratio (Δ/Σ) two-dimensional plot.

the slope of the monopulse function becomes very steep as a consequence of the aforementioned almost total splitting (and no overlapping) of the two individual tilted beams.

The behavior of the monopulse function with the distance is evidenced when the equi-monopulse contour curves are plotted in 2D around the monopulse array, as shown in Fig. 7. The FoV zone where the monopulse function presents no ambiguity is enclosed by the red dashed line, showing the aforementioned spatial compression in the close vicinity of the array. Once this near-field electromagnetic behavior has been electromagnetically studied, in the next section we evaluate the practical effects in the estimation of the DoA using the amplitude monopulse technique.

III. DoA ESTIMATION USING DISTANCE-DEPENDENT MONOPULSE FUNCTIONS

Once the RSSI or received power is acquired for both Σ and Δ channels of the monopulse array, the DoA is estimated as:

$$\text{DoA} = \theta \xrightarrow{\text{yields}} \min \left\{ \left| \Psi(\theta, r) - \frac{\Delta_m}{\Sigma_m} \right| \right\} \quad (4)$$

where Σ_m and Δ_m are the power levels measured at the sum and difference channels. As it can be seen, Eq. (4) depends on the distance r selected to estimate the DoA, since the

FIGURE 8. Theoretical DoA estimation for different radial distances, using the monopulse function characterized at $r = 3$ m.

monopulse function has proved to be dependent on distance in the near-field range. Typical monopulse systems operate in the far-field region and therefore a unique monopulse function can be used to estimate the DoA, independently on the radial distance.

This is not true for the case of proximity sensors, as it is illustrated in Fig. 8a where the DoA is estimated at different distances r and using the monopulse function characterized for a far-field distance of $r = 3$ m. The corresponding estimation error is plotted in Fig. 8b. As shown in Fig. 8, the theoretic DoA estimation is perfect and the error is null when the target is located at $r = 3$ m, which coincides with the distance used to characterize the monopulse function. However, as the target gets closer to the monopulse array, the DoA estimated using the far-field monopulse function is less accurate, showing an angular error of $\pm 5^\circ$ for $r = 1$ m, which increases to $\pm 7^\circ$ for $r = 50$ cm, and up to $\pm 10^\circ$ for $r = 25$ cm. Therefore, it is proved that the far-field patterns cannot provide accurate monopulse DoA estimation in the near-field range.

In Fig. 9, a similar DoA estimation test is performed but now using the monopulse function characterized at a near-field distance of $r = 50$ cm. Now, the estimation error is zero when the target moves in this calibration near-field distance of 50 cm. The DoA estimation becomes more inaccurate as the target moves to further distances into the far-field zone. A maximum DoA estimation error of $\pm 7^\circ$ is observed at a far distance of $r = 3$ m, when using the near-field monopulse function characterized at the distance of $r = 50$ cm. Besides, it must also be remarked that in the near-field zone, the FoV is compressed to $\pm 15^\circ$ (see Fig. 6), so that the DoA estimation error strongly increases out from this limited angular zone, as shown in Fig. 9. These results demonstrate that, for accurate DoA estimation using the monopulse technique in the near-field zone, it is needed a range-dependent monopulse function (3) which takes into account the fluctuations observed in the monopulse patterns as a function of distance.

FIGURE 9. Theoretical DoA estimation for different radial distances, using the monopulse function characterized at $r = 50$ cm.

FIGURE 10. Flow chart for range-dependent DoA estimation.

In Fig.10, we propose a distance-dependent monopulse DoA estimation algorithm. First, the distance r between the proximity sensor and the mobile device is estimated from the RSSI acquired at the sum channel Σ_m , and using RSSI-based ranging techniques [9], [10]. If the mobile is located in the far-field zone $r > d_{\text{FARFIELD}}$ given by (2), the conventional far-field monopulse function which is not dependent on distance can be applied to estimate the DoA. However, if the mobile is in the near-field range, the more satisfactory near-field monopulse function $\Psi(\theta, r)$ (3) must be applied to accurately estimate the DoA at the calculated distance r .

Another scenario where the near-field monopulse function must be used is the one in which the perpendicular distance between the proximity sensor and the mobile is fixed and previously known. This happens in corridor-like, conveyor belt and security gates scenarios, when the sensor is ceiling-mounted at a given height, or when the sensor is mounted on a wall at a security distance from the corridor, as shown in Fig.11. In these cases, the distance H is fixed and known

FIGURE 11. Corridor-like scenarios with constant perpendicular distance H a) Lateral view of monopulse mounted on ceiling at height H b) Top view of monopulse mounted on wall with lateral security distance H .

FIGURE 12. Near-field monopulse functions for different perpendicular distances H as a function of longitudinal position x .

a priori, and the mobile moves only in one direction x . As the mobile moves along different positions x , the distance r and the DoA angle θ are geometrically related as:

$$r = \frac{H}{\cos\theta}; \quad x = H \cdot \tan\theta \quad (5)$$

Therefore, in these cases it is practical to define a near-field monopulse function which depends on x for any value of H , and which allows to estimate the relative Cartesian shift x :

$$\Psi(x, H) = \frac{\Delta(x, H)}{\Sigma(x, H)} \quad (6)$$

This is shown in Fig.12 for different distances H . It must be noticed that these near-field monopulse functions are calculated taking into account that, for each longitudinal position x , not only the subtending angle θ varies, but also the radial distance r changes according to (5). As shown in Fig.12, lower values of H shorten the longitudinal zone which can be sensed, referred to as the longitudinal FoV (LFoV) in cm. The LFoV in the x direction reduces from 2 meters for $H = 2$ m, to LFoV = 90 cm for $H = 1$ m, and to LFoV = 40 cm for $H = 50$ cm. These results are in accordance with the 2D monopulse FoV plots previously showed in Fig.7.

On the other hand, higher spatial resolution is obtained for lower distances H , as it can be seen from the steep slope of the monopulse function $\Psi(x)$ for $H = 50$ cm in Fig.12. In any case, the near-field monopulse functions take into account the near-field effects for an accurate angular position estimation. In the following Section, we experimentally corroborate these theoretical results using a practical WiFi monopulse sensor operating in the near-field zone.

FIGURE 13. Picture of WiFi monopulse sensor [24] tested in chamber.

IV. EXPERIMENTAL VALIDATION

A practical monopulse array for WiFi DoA estimation designed in [24], is characterized in the near-field zone. The antenna array has a maximum dimension $S = 45$ cm -depicted in Fig.13- and operates in the WiFi 2.45 GHz band. Therefore, all previous theoretical results apply, and the near-field radiation range is limited between 50 cm and 3.3 m.

The monopulse system is tested in an anechoic chamber. A WiFi Access Point (AP) is configured to continuously send WiFi beacon frames, every 100 msec. and with 0 dBm power using channel 6 (2.437 GHz). In this way, we ensure a reference transmitter with constant emitted power and permanent traffic. The monopulse antenna is connected to a WiFi MiMo card which sniffs WiFi frames as explained in [24]. The RSSI levels of WiFi frames received at the sum Σ and difference Δ monopulse channels, are measured as a function of angle for different radial distances ($r = 3$ m, 2 m, 1 m, 50 cm and 25 cm). As shown in Fig.14, the measured RSSI angular patterns are in good agreement with the theoretical radiation patterns (Fig.5), demonstrating the expected near field distortion. As we get in close proximity to the array, the Σ and Δ patterns broaden, and eventually a dip is created in the perpendicular direction ($\theta = 0^\circ$) of the sum pattern Σ .

The corresponding digital (WiFi RSSI-based) monopulse functions as a function of radial distance r , are plotted in Fig.15. Again, good agreement is found between experiments and theory. As expected, the monopulse function is not stable with distance due to the near-field effects, showing a steeper angular slope and a narrower FoV as we approximate to the antenna array, in accordance with the theoretical plots in Fig.6.

Using these near-field monopulse functions $\Psi(\theta, r)$, the DoA can be estimated for different distances. To avoid multipath effects, the first DoA estimation experiments are performed inside the anechoic chamber. Fig.16 shows the measured DoA estimation error using the far-field monopulse function (the one in Fig.15 for $r = 3$ m), while approaching the antenna array. The dots in Fig.16 represents different

FIGURE 14. Measured RSSI levels at the sum (Σ) and difference (Δ) channels of the WiFi monopulse-array as a function of angle and radial distance.

FIGURE 15. Measured near-field digital monopulse functions.

error measurements at distinct angular positions inside the anechoic chamber, while the average error is plotted with a solid line. The RMSE (root mean square error) of the DoA estimation for each distance in Fig.16 is summarized in the first row of Table 1. It must be noticed that the WiFi monopulse reader reports an angular uncertainty of $\pm 2.5^\circ$ due to digital quantization of RSSI digital levels [24]. This creates a systematic error which limits the resolution to this $\pm 2.5^\circ$ value as shown in Fig.16 for a measuring distance $r = 3$ m, and corresponding to a RMSE of only 0.7° . Then, the estimation error increases as we get in closer proximity to the array due to the near-field effects. Experiments are in good concordance with theoretical results shown in Fig.8. For $r = 1$ m, the angular peak error augments in a extent of 3° thus creating an accumulated peak error of $\pm 5^\circ$ (RMSE 2°), which increases to $\pm 7^\circ$ for $r = 50$ cm, and up to $\pm 11^\circ$ for $r = 25$ cm (RMSE 6°).

If we use the near-field monopulse function for $r = 50$ cm, the DoA estimation errors are plotted in Fig.17 at different distances. The RMSE for these experiments are summarized in the fourth row of Table 1. As expected, the minimum error (RMSE 1.4°) is obtained when the mobile device is located at this nearby distance of 50 cm. In accordance with the

FIGURE 16. Measured DoA estimation error for different radial distances, using the monopulse function characterized at $r = 3$ m.

FIGURE 17. Measured DoA estimation error for different radial distances, using the monopulse function characterized at $r = 50$ cm.

TABLE 1. RMSE of DoA estimation (deg) as a function of radial distance r .

Monopulse function	measuring distance r , FoV = 60°				
	3 m	2 m	1 m	50 cm	25 cm
$\Psi(\theta, r=3m)$	0.7°	1.7°	2.0°	3.6°	6.0°
$\Psi(\theta, r=2m)$	1.7°	1.0°	2.1°	3.5°	6.2°
$\Psi(\theta, r=1m)$	1.9°	2.1°	0.9°	2.0°	4.5°
$\Psi(\theta, r=50cm)$	3.6°	3.5°	2.2°	1.3°	3.4°
$\Psi(\theta, r=25cm)$	5.9°	6.1°	4.4°	3.7°	1.4°

theoretical plots in Fig.9, this error increases as we move away from the array. A maximum RMSE of 3.6° is now observed for the further distance of $r = 3$ m due to the near-to-far field aberration effects. In the closest distance of $r = 25$ cm, the estimated DoA presents a RMSE of 3.4°. It must be noticed that this error at 25 cm using the near-field monopulse function for $r = 50$ cm, is lower than the one of 6.0° reported when using the far-field monopulse function with $r = 3$ m.

Also, it must be noticed that the mean error curves plotted with lines in Fig.16 and 17, follow the predicted dependence with the angle of observation for all the performed tests (see theoretical plots in Fig.8b and Fig.9b, respectively). Basically, the mean error is null at boresight direction (DoA 0°), and increases for higher angular directions. In any case, the best DoA estimation performance for any distance r in the entire FoV, is obtained when the adequate monopulse function is used, as highlighted in green color in Table 1.

To mitigate the DoA estimation inaccuracies due to near-field effects, we implement the range-dependent monopulse

FIGURE 18. Measured RSSI level at Σ channel as a function of distance.

estimation algorithm sketched in Fig.10. The acquired RSSI level at the sum pattern Σ , for different measuring distances and angles is shown in Fig.18. Also, the curve obtained from a simple spherical-wave propagation model is plotted for reference. From the measured RSSI level and using the average curve plotted in red, the radial distance r can be anticipated to use the appropriate monopulse function $\Psi(\theta, r)$.

The result of this range-dependent DoA estimation is plotted in Fig.19. The obtained RMSE values correspond to the data highlighted in green in the diagonal of Table 1. Now, for any distance ranging from 3 m to 25 cm, all the individual experiments show an RMSE below 1.5° at any direction within the FoV. The averaged DoA estimation error plotted in Fig.19 is null at any distance when using the appropriate monopulse function. As explained in [24], the RSSI levels

FIGURE 19. Measured DoA estimation error for different radial distances, using the corresponding range-dependent monopulse functions.

FIGURE 20. Picture of WiFi angle-sensitive proximity sensor mounted in a security shelf.

are discretized in 1-dBm steps, and this creates oscillations of $\pm 2.5^\circ$ in the DoA estimation around this null average error.

If the near-field effects are not considered and it is used the conventional monopulse function for far-field angular estimation (as done in long-range RADARs [16]), the average angular error plotted in Fig. 16 can increase up to 11° at short distances, with corresponding RMSE growing up to 6° as summarized in Table 1.

Once it has been demonstrated in an anechoic chamber the necessity to consider the near-field effects to estimate the DoA for short distances, a practical outdoor scenario as the one shown in Fig. 20 is tested. As it was sketched in Fig. 11a, security-gate proximity sensors can be ceiling-mounted at a given height H . In our case we have located the proximity angular sensor on a security shelf, at a short height H from the mobile WiFi devices to be sensed.

FIGURE 21. Measured near-field monopulse functions as a function of longitudinal position x , for different perpendicular distances H .

The near-field longitudinal monopulse function $\Psi(x, H)$ (6) characterized in the anechoic chamber at three different distances $H = 2$ m, 1 m and 50 cm are plotted in Fig. 21. As expected from theory (see Fig. 12.), the longitudinal FoV (LFoV) narrows and the spatial resolution (slope) increases as the height H is shortened. These functions are used to estimate the position of three different WiFi devices: the same AP used in the anechoic chamber (see Fig. 13), and two smartphones as illustrated in Fig. 20.

The WiFi packets transmitted by the mobile devices are collected by the WiFi monopulse reader, which compares the measured sum and difference RSSI values (Σ_m and Δ_m), with the near-field monopulse function $\Psi(x, H)$ to estimate the x position:

$$\text{Position} = x \xrightarrow{\text{yields}} \min \left\{ \left| \Psi(x, H) - \frac{\Delta_m}{\Sigma_m} \right| \right\} \quad (7)$$

In a first experiment, the WiFi monopulse reader is mounted at a height $H = 50$ cm above the floor, so that a LFoV of ± 25 cm can be sensed. The three mobile devices (access point, smartphone 1 and smartphone 2) are located at different x positions within this LFoV. Fig. 22 shows the estimation error in cm for the three WiFi mobile devices under test, and using monopulse functions characterized at different heights. Table 2 summarizes the RMSE in the location estimation. Accurate proximity location with peak errors below ± 6 cm in the entire 50 cm LFoV and a with a RMSE value below 4 cm, is obtained for the three devices when the appropriate near-field monopulse function $\Psi(x, H = 50 \text{ cm})$ is used. However, if we use the monopulse function characterized for $H = 1$ m the peak errors increase up to ± 25 cm (RMSE 18.5 cm), and up to ± 70 cm (RMSE 57 cm) when using the monopulse for $H = 2$ m.

The experiment is repeated for a higher distance $H = 1$ m, reporting the results in Fig. 23 in an extended LFoV of ± 55 cm in the x direction. Now, the most accurate position estimations are obtained when the correct near-field monopulse function $\Psi(x, H = 1 \text{ m})$ is chosen, showing a maximum peak error of ± 15 cm (RMSE below 6.8 cm) for any of the three studied WiFi devices. As expected, the minimum error has increased for this higher H when compared

FIGURE 22. Position estimation error for the set-up in Fig.20 with $H = 50$ cm.

TABLE 2. RMSE of position estimation (cm) as a function of height H and for three different WiFi devices.

Monopulse function	measuring height $H = 50$ cm, LFoV = 50 cm		
	Access Point	Smartphone1	Smartphone2
$\Psi(x, H=2m)$	57.0 cm	52.9 cm	49.2 cm
$\Psi(x, H=1m)$	18.5 cm	17.9 cm	16.1 cm
$\Psi(x, H=50cm)$	3.1 cm	1.8 cm	3.8 cm
Monopulse function	measuring height $H = 1$ m, LFoV = 110 cm		
	Access Point	Smartphone1	Smartphone2
$\Psi(x, H=2m)$	31.9 cm	38.1 cm	27.3 cm
$\Psi(x, H=1m)$	4.4 cm	5.1 cm	6.7 cm
$\Psi(x, H=50cm)$	17.9 cm	17.0 cm	19.9 cm

to the case $H = 50$ cm, due to the lower resolution of $\Psi(x, H)$ -lower slopes in Fig.21- as H rises. This error grows if the correct monopulse function is not selected, as it can be seen in Fig.23 for the cases $\Psi(x, H = 2$ m) and $\Psi(x, H = 50$ cm), which report higher location errors of ± 65 cm (RMSE 38.1 cm) and ± 35 cm (RMSE 19.9 cm), respectively. In all cases, the estimation errors in Figs. 22 and 23 are higher for locations away from the perpendicular direction of the sensor, following the tendency shown for the DoA estimation error in Figs. 16 and 17.

Therefore, it has been proved that the studied angular-sensitive monopulse sensor can provide accurate directional proximity estimation if the appropriate near-field monopulse functions are considered. The system is able to estimate the actual location within a root mean square error below 4 cm

FIGURE 23. Position estimation error for the set-up in Fig.20 with $H = 1$ m.

TABLE 3. Near-field ranges of reported monopulse systems used for IoT applications.

Ref.	frequency	Monopulse array size S	$d_{\text{NEARFIELD}}$ (1)	d_{FARFIELD} (2)	FoV
[17]	867 MHz	54 cm	42 cm	1.7 m	$\pm 40^\circ$
[18]	915 MHz	37 cm	24 cm	83 cm	$\pm 30^\circ$
[19]	920 MHz	18 cm	8 cm	20 cm	$\pm 20^\circ$
[20]	868 MHz	60 cm	49 cm	2 m	$\pm 40^\circ$
[21]	2.3 GHz	30 cm	28 cm	1.3 m	$\pm 45^\circ$
[22]	2.45 GHz	9 cm	5 cm	14 cm	$\pm 45^\circ$
[23]	2.45 GHz	30 cm	30 cm	1.5 m	$\pm 40^\circ$
[24]	2.45 GHz	45 cm	50 cm	3.3 m	$\pm 30^\circ$

in the entire LFoV of 50 cm for a near-field height of $H = 50$ cm, and with an RMSE below 7 cm for $H = 1$ m, and for any of the three WiFi devices as highlighted in green in Table 2. Far-field assumptions are not valid at these close distances, leading to high DoA estimation errors and thus considerable proximity location inaccuracies.

For the authors' knowledge, it is the first time that the amplitude-monopulse angular estimation technique is applied for near-field angular-sensitive proximity detection. As summarized in Table 3, the near-field region of many of the monopulse systems proposed in recent designs for RFID/ WLANs systems, extends to a remarkable range of distances where these near-field effects cannot be ignored. The extension of the near-field zone is enlarged as the antenna size is greater, as happens for directive-beamed arrays which

provide high DoA resolution as the one studied in this paper. As done in near-field RFID antennas [32], [33], it is important to consider the near-field effects to predict the actual digital reading performance of directive proximity sensors.

V. CONCLUSION

The estimation of the direction of arrival (DoA) using monopulse techniques, has been studied for the case of proximity angular sensors. The amplitude monopulse technique offers simplicity to estimate the DoA with good angular resolution, using RSSI information which is directly available using commodity hardware and a low-cost array of two directive antennas. However, monopulse systems have been typically used in the far-field zone of the antenna array (for instance in long-range monopulse RADAR systems), where the monopulse function is stable with distance. As demonstrated in this paper, this is not the case for monopulse sensors used in proximity-aware applications for Smart Spaces, where the IoT / smartphones mobile devices can be in the near-field zone of the monopulse array.

The near-field effects in the proximity of a practical angle-sensitive proximity WiFi monopulse array operating in the 2.45 GHz band have been evaluated. The experimental results are consistent with electromagnetic theory, showing that far-field sum and difference patterns distort in the proximity of the sensor, making the monopulse functions strongly dependent on the radial distance. It has been shown that high DoA estimation errors of more than 10° appear close to the sensor, if the conventional far-field monopulse function is used when sensing in the near-field radiative zone (which in our case extends from 50 cm to 3 meters from the array). Thus we have proposed the use of a range-dependent near-field monopulse function $\Psi(\theta, r)$ which takes into account the near-field range effects, and estimates the DoA with higher accuracy.

Similarly, the monopulse function can be defined in Cartesian near-field coordinates, i.e. $\Psi(x, H)$, to estimate the proximity position x with good accuracy in the immediacy of the monopulse array. For that, the perpendicular distance H must be fixed and known, as happens in security gates. These concepts have been experimentally demonstrated with a practical angle-sensitive proximity WiFi sensor, proving the mitigation of the near-field aberration effects to estimate with accuracy the direction and contiguity location of mobile devices at close distances from the monopulse array.

The proposed technique has proved a DoA estimation root mean square error below 1.5° in a FoV of 60° , and for a range of distances from 50 cm to 3 meters of the sensor. This translates to a root mean square error below 4 cm over a linear FoV of 50 cm, when locating real WiFi devices from a height of $H = 50$ cm. The location RMSE increases to 7 cm when covering a wider linear FoV of 110 cm from a height of $H = 1$ m. Although the results of this paper have been applied for a particular WiFi monopulse proximity sensor, the reported considerations are valid for any monopulse system operating in the near-field zone, and using any alternative wireless technology such as Bluetooth, Zigbee or RFID.

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Artículo 3

Wi-Fi RTT-Based Active Monopulse RADAR for Single Access Point Localization

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Wi-Fi RTT-Based Active Monopulse RADAR for Single Access Point Localization

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ABSTRACT The purpose of this work is to implement a novel active radar system for single access point two-dimensional localization system based on 802.11 wireless local-area networks (WLAN). The active radar employs the 802.11 Fine Time Measurement (FTM) Round Trip Time (RTT) as specified in the 2016 update of WIFI Standard to calculate the ranging distance and acquires two channels of Received Signal Strength Indicator (RSSI) to estimate the azimuthal angle. In this way, real-time two-dimensional localization of Wi-Fi RTT-compatible mobile Internet of Things devices is demonstrated using a single access point operating in the 2.4GHz band. The experimental results performed in anechoic chamber and in a real environment point up a mean positioning error below one meter within a Field of View (FoV) of 60° and distances up to 14 meters, with an acquisition time below 0.5 seconds.

INDEX TERMS Localization with 802.11, active Wi-Fi radar, round trip time (RTT), angle of arrival (AoA), amplitude monopulse radar.

I. INTRODUCTION

Real-time localization systems (RTLS) is one of the key enabling technologies for efficient Internet of Things (IoT) applications and services [1]. More particularly, RTLS for mobile devices connected to wireless local-area networks (WLAN) based on the globally spread 802.11 Wi-Fi protocols have been widely proposed [2] as an indoor localization option when the Global Navigation Satellite System (GNSS) cannot be precisely employed. Regarding indoor environments, RTLS can be divided into fingerprinting (FP), Time of Arrival (ToA), and Angle of Arrival (AoA). In the last years, FP has been one of the most predominant indoor location techniques [3]–[5] because every Wi-Fi card adapter provides RSSI values. The main drawback of this technique is that they rely on an extensive and time-consuming off-line

calibration phase [6] and the variations over the time of fingerprint in a large building require periodic recalibrations [7]. ToA ranging methods require at least three Access Points (APs) for triangulation techniques, and it can be based on Received Signal Strength Information (RSSI) [8], [9], or on the measure of the time-of-flight of the communications accessing by the Channel State Information (CSI) [10] of the Wi-Fi card. This technique, widely used in high-bandwidth location systems like UWB, has the handicap of lower performance in a higher multipath environment [11]. Moreover, a small error in the time measures causes a significant error in the computed distance because of the speed of light. For this reason, CSI-based techniques require complex calibration for synchronization and/or modifying the hardware/software to acquire complex CSI / IQ data to obtain Time-of-Flight information. The estimation of AoA usually requires to employ array antenna systems [12] along with complex signal processing techniques [13], [14] where the IQ information from

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the signal is involved. However, another approach to estimate AoA from accessible RSSI data can be found in the literature [15], [16].

Furthermore, related to the ToA location techniques for smartphones devices, a new scenario has been established with the adoption of the 802.11mc (Wi-Fi Fine Time Measurement, FTM) standard [17] by the Android smartphone Android 9 and higher releases [18]. According to the Wi-Fi Alliance, an accuracy in meters' level can be reached with this standard employing the Round-Trip-Time (RTT) procedure. A complete empirical analysis of the FTM protocol was performed in [19], and in [20], [21] location systems employing RTT and inertial sensors from smartphones are depicted.

All the aforementioned works required several APs to localize IoT devices. In most cases, the higher the number of APs, the better the accuracy of the systems. Nevertheless, in the IoT paradigm, under some premises such as smart-connected home [22], only one single or few APs are available to implement services based on the precise ubication of the inhabitants of the home.

In this context, several two-dimensional localization systems based on a single Wi-Fi AP can be found in the scientific literature. To the best of our knowledge, CUPID [23] is the first proposal of a single-AP indoor location algorithm using commodity APs. The position of a smartphone employing CUPID is determined by a combination of ranging and AoA obtained by accessing to CSI. An improved version from the same authors of CUPID is SAIL [24]. In this work, the range estimations are based on the use of ToF computed by accessing to CSI together with a dead reckoning system based on a Kalman Filter implemented on Android smartphones. Another single AP location ToF-based algorithm is Chronos [25]. It reaches decimeters accuracy employing MIMO (Multiple-Input Multiple-Output) two antennas commercial devices. This accuracy in the ToF estimation is achieved with the implementation of channel hopping and combining the 35 different frequency bands as a wideband radio. The implementation requires driver modification of the Wi-Fi card driver for the channel hopping, and it is out of the Wi-Fi standard. Similar to Chronos, the S-Phaser implementation [26] is a frequency hopping system. Nonetheless, it only uses two different channels. In detail, S-Phaser employs CSI data and a proposed Interpolation Elimination Method (IEM) to remove the phase and angle error of the direct path of the signal. Afterward, it implements the Broad-band Angle Ranging (BAR) to determine the transmitter distance and triangulation techniques to determine the location.

Another ToF related to single AP work is SiFi [27]. It utilizes a three-antennas MIMO single channel and a single AP indoor location protocol built with commodity hardware. As opposed to [23], [24], SiFi does not require extra information from smartphone sensors. However, it requires access simultaneously to the CSI of the three antennas of the MIMO Wi-Fi card during the communication and cannot be employed in real-time applications due to the latency of the Linux CSI Tool and the computation complexity. Another key

drawback is that only one device can be located at a time. Splicer [28] is also in the bucket of CSI single AP location system. It is based on the power delay profiling of the CSI measures and can be implemented with only one commodity Wi-Fi AP. The algorithm needs collecting the CSI of several packets at different frequencies. Thereby, channel hopping method is required. With the power delay profile system, the ranging to the devices can be precisely computed.

Some other works implement single AP indoor location systems using directly accessible RSSI, thus avoiding the need of CSI data. The work [29] employs Switched Beam Antenna (SBA) with eight dual Wi-Fi directional antennas to implement a simultaneous range together with AoA system with the RSSI. Similarly, in [30], RSSI data collected from a SBA is used in conjunction with motion sensors to compute the precise location. Therefore, all previous single AP Wi-Fi localization systems are developed according the bases of signal processing, which in turn integrates complex CSI acquisition / phased-array techniques [23]–[28], or on more straightforward RSSI processing at the cost of using complex electronically switchable antenna arrays [29]–[30].

The main contribution of this work is the demonstration for the first time of the conception of a simple active RADAR for Wi-Fi RTLS using a single access point (AP), which does not require complex CSI data or expensive phased-array / switched beam antennas. This digital radar is conceived under the premises of the 802.11mc RTT protocol to estimate the range distance and a monopulse antenna to estimate the azimuthal angle from the measured RSS (Received Signal Strength) levels. To the best of our knowledge, this is the first work where both technologies have been combined for location purposes. Section II describes this digital Wi-Fi RTT monopulse RADAR, and its calibration phase in the anechoic chamber is detailed in Section III. The real-time two-dimensional localization performance in an outdoor scenario is evaluated in Section IV, showing a mean positioning error below 1 meter within a Field of View of 60° and distances up to 14 meters, with an acquisition time below 0.5 seconds. Finally, Section V compares this active Wi-Fi RADAR with other single access point Wi-Fi RTLS proposals described in the literature and, finally, summarizes the main conclusions of this work and future lines to improve this innovative IoT indoor localization system.

II. WI-FI RTT MONOPULSE SYSTEM DESCRIPTION

Classical monopulse RADAR systems have been used for decades to estimate the range distance and angular location of mobile objects from the received echoes [31]. More recently, MIMO RADAR systems are being developed for passive target tracking [32]. Our novel monopulse Wi-Fi system is based on this concept, and can be understood as an active digital version of classical passive monopulse RADAR. It is an active RADAR since the range distance is not measured from the passive reflection of transmitted echoes, but on active communication using 802.11mc Wi-Fi Fine Time Measurement (FTM) standard [17]. This FTM standard allows

digital Round-Trip-Time (RTT) measurements, which would be equivalent to the analog radio-frequency (RF) echo two-way travel time, from which the range distance R can be calculated with a meters' level accuracy [19]–[21]. In addition, the Wi-Fi RSSI-based monopulse technique proposed in [15], [16] can be used to estimate the azimuthal bearing angle ϕ associated to the Direction-of-Arrival (AoA). Therefore, range R and AoA angle ϕ estimation based on active digital Wi-Fi metrics (RTT and RSSI, respectively) are combined, and once the distance and the angle are obtained, the precise (x, y) position can be directly computed as in analog RF microwave monopulse RADAR.

FIGURE 1. Scheme of the proposed Wi-Fi RTT active monopulse RADAR.

The scheme of the system is illustrated in Fig. 1, showing a single 2×2 MIMO 802.11mc Wi-Fi AP which is connected to two antennas (namely antenna left and right) in tilted monopulse configuration [16]. As previously described, by communicating with a RTT-compatible mobile device, the RTT and the RSSI acquired by each antenna are processed in a personal computer to estimate the range distance R and the azimuthal AoA ϕ , and eventually the 2D position $\{x, y\}$, as also illustrated in Fig. 1.

FIGURE 2. 802.11mc fine time measurement (FTM) protocol for RTT acquisition.

Regarding the 802.11mc standard to obtain the RTT, it is based on the FTM protocol [17]. This is a device-to-device location protocol that requires that an initiator (in our case a smartphone, but it can be any other IoT device) asks for a ranging request to a responder, which is a Wi-Fi AP. The protocol is illustrated in Fig. 2. The first message frame sent by the initiator to the responder is labeled as FTM request. When the request is received by the responder, it dispatches an acknowledge (ACK) frame to the initiator. This initiates an exchange of two FTM-ACK frames from which the RTT can be calculated from the associated timestamps t_1, t_2, t_3 and t_4 summarized in Fig. 2a, following the next relation:

$$RTT = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} \quad (1)$$

This process can be repeated as a burst of n RTT-ACK frames, as shown in Fig. 2b, to increase the RTT estimation accuracy as follows:

$$RTT = \frac{1}{n} \left(\sum_{k=1}^n t_4(k) - \sum_{k=1}^n t_1(k) \right) - \frac{1}{n} \left(\sum_{k=1}^n t_3(k) - \sum_{k=1}^n t_2(k) \right) \quad (2)$$

For each of the FTM requests from an initiator, the above protocol has to be executed. Once the RTT is computed, the range R is estimated by multiplying the time by the speed of light c_0 and applying a correction factor R_{OFFSET} which must be calibrated a priori [19]:

$$R = RTT / 2 \cdot c_0 + R_{OFFSET} \quad (3)$$

This result is obtained by the initiator without the requirement of being connected to the AP, and it is implemented in Android via API. This is an easy-to-use already available technology present in commodity APs and mobile devices which are compatible with the 802.11mc standard, in contrast to less accessible Time-of-Flight estimation based on hardware modification for AP synchronization or CSI acquisition [23]–[28]. In our case, we use a Yocto Wild AP [33] equipped with a MIMO Wi-Fi chipset Intel 8260AC as the FTM-compatible responder. As initiator, we use an Asus Rog Phone II with the Qualcomm® Snapdragon™ 845, which is a 802.11mc compatible smartphone. They are shown in the picture of Fig. 3.

FIGURE 3. Picture of Wi-Fi RTT active monopulse RADAR in anechoic chamber.

Regarding the estimation of the azimuthal AoA angle ϕ , the monopulse power-based technique [31], [32] employing two tilted antennas, has recently demonstrated a good estimation of the AoA for Wi-Fi low-cost systems [16]. Its main advantage, when compared to other Wi-Fi AoA techniques applying complex CSI data for AoA estimation [23]–[28], is that directly accessible RSSI data is used for the AoA processing. In our case, we connect the MIMO Wi-Fi AP to two commercial panel antennas [34], which are as antenna left and antenna right in the scheme of Fig.1, and they are also depicted in the picture of Fig.3.

The monopulse technique is based on the different power levels received at each one of the two tilted antennas, depending on the azimuthal ϕ AoA of the Wi-Fi signal emitted by the device. With the RSSI measured by each antenna as a function of the incoming angle ϕ , the sum (Σ) and difference (Δ) patterns are generated. Besides, it must be taken into account that smartphone localization using Wi-Fi systems can operate in the near-field radiation region of the monopulse antennas [35], and therefore the monopulse function must be calibrated for different radial distances R inside this near-field zone, and also for the far-field region. The monopulse function $\Psi = \Delta/\Sigma(\phi, R)$ is defined in expression (4), where $K_D(R)$ is a correction factor which must be calibrated as a function of distance [35].

$$\Psi(\phi, R) = \frac{\Delta(\phi, R)}{\Sigma(\phi, R)} = \frac{RSSI_R(\phi, R) - K_D(R) \cdot RSSI_L(\phi, R)}{RSSI_R(\phi, R) + K_D(R) \cdot RSSI_L(\phi, R)} \quad (4)$$

To estimate the AoA angle ϕ , the RSSI acquired by each antenna of the MIMO AP is read and the monopulse value Ψ_{RSSI} is calculated in (5). Then a direct numerical search is performed to obtain the estimated AoA ϕ_{EST} which minimizes the monopulse comparison error function defined in equation (6):

$$\Psi_{RSSI} = \frac{\Delta_{RSSI}}{\Sigma_{RSSI}} = \frac{RSSI_R - K_D \cdot RSSI_L}{RSSI_R + K_D \cdot RSSI_L} \quad (5)$$

$$DoA = \phi_{EST} \xrightarrow{\text{yields}} \min |\Psi(\phi_{EST}, R) - \Psi_{RSSI}| \quad (6)$$

III. RANGING AND ANGULAR CALIBRATION

As described, both the RTT estimation (1)–(3) and the AoA estimation (4)–(6), need a calibration phase before the estimation process can be initiated. This calibration is performed in an anechoic chamber as shown in Fig.3, which allows to measure angular radiation patterns as a function of the distance between $R = 50\text{cm}$ and $R = 3\text{m}$.

The calibration steps are sketched in Fig.4. First, the offset R_{OFFSET} in equation (3) must be calibrated to carry out accurate evaluation of the RTT and thus precise estimation of the ranging distance R . For that, the RTT is measured in the anechoic chamber as a function of the radial distance R and for different angular directions ϕ . The experiments have been performed in channel #6 (2.437 GHz) with a 20MHz bandwidth. The measurements are depicted in Fig.5. This figure shows an offset $R_{OFFSET} = 600\text{cm}$ is the more suitable

FIGURE 4. Steps in the calibration process.

FIGURE 5. Measured ranging distance R after calibration of the RTT offset.

for all the ranging distances from $R = 50\text{cm}$ to $R = 3\text{m}$. As can be seen, the estimated RTT ranging error is more significant for shortest distances $R = 1\text{m}$ and $R = 50\text{cm}$. Also, it can be observed that the estimation error increases for angles of observation higher than $\phi = \pm 60^\circ$. As will be shown, this is related to the Field of View (FoV) of the monopulse antennas, which gain strongly decreases out of this angular zone. In any case, the calibrated RTT offset is established to the fixed value $R_{OFFSET} = 600\text{cm}$, as summarized in Table 1. This fixed value must be independent of the unknown distance R and AoA angle ϕ , since it will be used to estimate the ranging R and the AoA direction ϕ .

The next step is to calibrate the monopulse functions as a function of the ranging distance R and the azimuthal angle ϕ , following equations (4)–(6). To this end, the digital sum $\Sigma(\phi, R)$ and difference $\Delta(\phi, R)$ patterns shown in Fig.6 are characterized by acquiring the RSSI levels at the left and right antennas, which in turn depend on the azimuthal angle and the ranging distance R .

The measured normalized RSSI angular patterns are plotted in Fig.6 for the same ranging distances from $R = 50\text{cm}$ to $R = 3\text{m}$ as in Fig.5. As described in [35], the angular patterns vary due to the near-field effects, and this must be considered for accurate angular estimation in short distances. In our case, the near-field zone reaches up to $R = 2.5\text{m}$; for larger distances the far-field patterns obtained for $R = 3\text{m}$ can be used. Similarly, the correction factor $K_D(R)$ in (4) must be properly calibrated for distances in the near-field zone, in order to obtain accurate monopulse functions. The values

FIGURE 6. Measured sum and difference patterns as a function of ranging distance R after calibration of the monopulse offset.

TABLE 1. Calibration of RTT Offset R_{OFFSET} and Monopulse Factor K_D .

Distance R (m)	R_{OFFSET} (cm)	K_D (dB)
3	600	-0.7
2	600	-1.0
1	600	-2.3
0.5	600	-4.0

of $K_D(R)$ to obtain the optimum calibrated normalized RSSI patterns in Fig.6 as function of the ranging distance R , are summarized in Table 1.

FIGURE 7. Measured monopulse functions as a function of ranging distance R after calibration of the monopulse offset.

Once the sum $\Sigma(\phi, R)$ and difference $\Delta(\phi, R)$ patterns, together with the monopulse correction factor $K_D(R)$, have been characterized in the anechoic chamber, the angular and range dependent monopulse functions $\Psi(\phi, R)$ (equation (4)) shown in Fig.7, are calibrated and recorded as summarized in the calibration process depicted in Fig.4. As explained in [35], the monopulse function shows an angular range without ambiguity, where it monotonically varies between -1 and $+1$, and which determines the FoV. As it can be seen in Fig.7, in our case the FoV is limited from $\phi = -30^\circ$ to $\phi = +30^\circ$. Within this FoV, both the AoA and the RTT ranging distance can be accurately estimated. Out from this FoV, the AoA estimation suffers from ambiguities, and as

it was shown in Fig.5, the RTT-based ranging also shows increased error in the distance estimation.

FIGURE 8. Flow-chart for ranging and AoA estimation process after calibration.

After the calibration phase, the estimation of the ranging distance R and the AoA angle ϕ , is accomplished by the algorithm sketched in Fig.8. First, the range R is estimated using the RTT FTM technique with the calibrated offset R_{OFFSET} . Once R is estimated, the AoA angle ϕ is estimated using the adequate monopulse function for this value of R . In particular, if $R < 2.5\text{m}$ (which is the near-field distance) the pre-recorded monopulse function $\Psi(\phi, R)$ must be applied. If the estimated range R extends further into the far-field zone, then the far-field monopulse function $\Psi(\phi, R = 3\text{m})$ can be used independently of the estimated distance.

As an example, the RTT range R and the AoA angle ϕ are estimated inside the anechoic chamber for different distances R , and the range and angular estimation error is plotted in Fig.9. As it was previously anticipated, the RTT-based distance estimation works better for larger distances and for angles within the FoV, showing an error below 10 cm for $R = 3\text{m}$ and $R = 2\text{m}$ and for angles between $\phi = -30^\circ$ and $\phi = +30^\circ$. For a shorter distance of $R = 1\text{m}$, this error increases up to 30cm and up to 60cm for $R = 50\text{cm}$, due to the aforementioned near-field inaccuracies.

Similarly, the AoA estimation shows an error below 5° inside this FoV $\phi = \pm 30^\circ$ and for distances above $R = 1\text{m}$. For $R = 50\text{cm}$, the near-field effects involves a higher error in the AoA estimation, up to 20° even within this FoV (see Fig.9d). In any case, out of the FoV, both range and AoA estimation present increased inaccuracies. The AoA estimation error increases up to 60° for angles well far from the FoV (see for instance $\phi = \pm 70^\circ$), and similarly the RTT-based distance estimation reaches error values up to 75cm. The increased AoA estimation error outside the FoV is mainly due to the fact that the monopulse function has a bi-univocal behavior only in the linear zone ranging from -30° to $+30^\circ$, as clearly shown in Fig.7 [16]. Outside this limited FoV, the AoA cannot be univocally guessed, leading to wrong angular estimates. Similarly, the RTT-based distance estimation performs better inside the FoV, where the panel antenna gain is greater. The FoV could be extended using scanning antennas, at the

FIGURE 9. Ranging and angular estimation error in anechoic chamber for different radial distances a) $R = 3$ m b) $R = 2$ m c) $R = 1$ m d) $R = 50$ cm.

expense of a more complex system which is out of the scope of this work. As described in [35], thanks to the correct guess of the near-field distance, the appropriate dependent monopulse function can be chosen and the AoA estimation error due to near-field effects can be strongly mitigated. This makes this localization system suitable to localize mobile devices at distances even when the far-field radiation zone is not guaranteed. This is of much importance for real WLAN scenarios, where the mobile devices can be located at short distances from the Wi-Fi AP.

The performance of this single-AP Wi-Fi RADAR system for two-dimensional localization in a real outdoor scenario is evaluated in the following Section.

IV. TWO-DIMENSIONAL LOCALIZATION

Once calibrated, the single-AP RTT Wi-Fi monopulse RADAR has been placed in an outdoor scenario to evaluate its performance for real-time two-dimensional localization of 802.11mc compatible mobile devices. A total area of $12\text{ m} \times 12\text{ m}$ is studied, using the $62\text{ cm} \times 70\text{ cm}$ floor tiles as a grid. This is sketched in the pictures of Fig.10, leading to a total of 304 sampling points. The AP is located at $x = 0\text{ m}$ $y = 0\text{ m}$, and for each sampling position with known coordinates, its distance R to the AP and its bearing angle ϕ are estimated to evaluate the two-dimensional positioning accuracy.

FIGURE 10. Experimental setup for outdoors localization with single-AP Wi-Fi RTT monopulse RADAR. a) Lateral view b) Front view c) Localization zone layout.

The blue lines in Fig.10c represent the limits of the angular FoV (from $\phi = -30^\circ$ to $\phi = +30^\circ$), while the red circles with radii $R = 0.5\text{ m}$, $R = 1\text{ m}$, $R = 2\text{ m}$, and $R = 3\text{ m}$ show the near-field zones of the RADAR system. To illustrate the real-time signal processing for localization, the data acquired during 45 seconds are analyzed for two illustrative positions of the mobile devices: point A inside the FoV and point B outside the FoV. The sampling rate is 450 miliseconds, so that a total of 100 samples are plotted in the 45 sec-long datagrams shown in Fig.11 and Fig.12 (for points A and B, respectively).

In Fig.10c, point A is located at coordinates $x = -1.875\text{ m}$, $y = 8.4\text{ m}$, which corresponds to $R = 8.6\text{ m}$ and $\phi = -12.6^\circ$.

FIGURE 11. a) Real-time Wi-Fi signal acquisition and b) RADAR estimation inside the FoV (point A in Fig.10c).

FIGURE 12. a) Real-time Wi-Fi signal acquisition and b) RADAR estimation outside the FoV (point B in Fig.10c).

inside the FoV. Fig.11a plots the RSSI acquired by each antenna connected to the MIMO Wi-Fi AP. As commented, every 450 msecs., the RSSI values are refreshed and processed in real-time using the amplitude monopulse technique to estimate the azimuthal AoA angle ϕ . Prior to that, the ranging distance R must first be estimated, to determine if the mobile is in the near-field or the far-field zone of the RADAR. The estimated distance R is plotted with continuous black line in Fig.11b, showing that it fluctuates above the real distance $R = 8.6\text{m}$ (dashed black line), with a maximum deviation to $R = 9.5\text{m}$ (this is, less than one meter error). Once the ranging distance is estimated, the location algorithm selects the appropriate monopulse function to estimate the AoA, as it was sketched in Fig.8. In this case, point A is in the far-field zone of the RADAR ($R > 2.5\text{m}$), so that the far-field monopulse function $\Psi(\phi, R = 3\text{m})$ is applied to estimate ϕ from the acquired RSSI data at each antenna. The estimated AoA is plotted with continuous red line in Fig.11b, and it is compared to the real AoA $\phi = -12.6^\circ$ (dashed red line).

In this case, since the point A is within the FoV, the estimated AoA shown in Fig.11b varies between $\phi = -14^\circ$ and $\phi = -20^\circ$, i.e. with a maximum error of 8° compared to the real AoA. It is remarkable that, despite the 5 dB variations in the acquired RSSI levels observed in Fig.11a, the estimated angle keeps stable with only this 6° fluctuation. As it can be seen in Fig.11a, the variations in the RSSI levels acquired from antenna left and antenna right are correlated. As it was explained in [16], the amplitude monopulse comparison technique absorbs the fluctuations due to fading, orientation, obstacles, etc. which affect similarly to both antennas, and which are not associated with a real AoA change.

The signals acquired for the point B, located at $x = +5\text{m}$, $y = 4.9\text{m}$ with $R = 6.5\text{m}$ and $\phi = +50^\circ$ outside the FoV, are analyzed in Fig.12. This time, both the estimation of distance and AoA suffer from higher errors. Particularly, the RTT FTM technique shows a mean error of 1.5m, estimating the distance around $R = 8\text{m}$. More remarkable is the AoA estimation error, which due to ambiguities outside the FoV estimates a false AoA around the perpendicular direction of the AP $\phi = 0^\circ$, leading to wrong location of the mobile device as shown by the point B' in Fig.10c.

To better illustrate the overall localization performance of the proposed RTT Wi-Fi monopulse RADAR system, the AoA estimation error, the ranging estimation error, and the eventual two-dimensional localization error (Euclidean distance error) are analyzed for the 304 sampling points covering the $12\text{m} \times 12\text{m}$ testing grid. The spatial distribution of the error is plotted as a heatmap in Fig.13. In particular, Fig.13a illustrates the AoA error, showing that inside the FoV this error keeps below 10° in most of the points, while outside the FoV the monopulse ambiguities strongly increase the uncertainty in the estimation of the AoA angle. The range estimation plotted in Fig.13b also suffers from higher error outside the FoV, although this is not so remarkable as for the AoA estimation. As commented, close to the AP ($R < 3\text{m}$), the RTT ranging estimation error is higher due to the near-field effects. Also, for distances above 10m the RTT inaccuracy increases; therefore, at a mid-distance ranging between $R = 3\text{m}$ and $R = 10\text{m}$ the RTT precision shows the best ranging estimation.

In any case, once the ranging R and the AoA angle ϕ have been estimated, the two-dimensional coordinates $\{x, y\}$ of the mobile device can be calculated. The Euclidean distance between the real location and the estimated coordinates is evaluated for each point, and the resulting spatial distribution of the localization error is plotted in Fig.13c. It is clearly distinguishable the difference in the performance inside and outside the FoV. The Cumulative Distribution Function (CDF) for each estimate (AoA, ranging, and Euclidean distance errors) is plotted in Fig.14 to summarize the system performance, distinguishing between inside the FoV, outside the FoV, and the whole zone performance.

Fig.14a illustrate the distribution of the CFD for the AoA error obtained from the monopulse function. It is demonstrated that 90% of the samples inside the FoV show less than

FIGURE 13. Spatial distribution of mean error in the estimation of a) angle of arrival ϕ , b) range distance R , and c) 2D location.

10° AoA estimation error, and 100% of the samples present an error below 28°. As summarized in Table 2, the corresponding root mean square error (RMSE) is below 6° and the mean error is below 5° for this FoV zone. Outside the FoV, the AoA estimation strongly deteriorates, reporting a 90% percentile with almost 65° error and 34° mean angular error. The CDF with the ranging errors measured from the RTT distance estimation is shown in Fig. 14b, reporting a 90% percentile of the samples inside the FoV with less than 1 meter deviation from their actual distance to the Wi-Fi AP. This ranging error 90% percentile increases up to 170cm outside

FIGURE 14. CDF for estimation error of a) angle of arrival ϕ , b) range distance R , and c) 2D location.

the FoV. As previously commented, the ranging estimation performance does not deteriorate so much out of the FoV zone, as it happened to the AoA estimation.

This is evident from the CDF curves, which show that the AoA CDF strongly worses outside the FoV in Fig 14a, while the RTT CDF in Fig. 14b keeps more stable although pointing out higher error outside the FoV. The associated RMSE and mean ranging error are summarized in Table 3, showing that inside the FoV the mean error is below 50cm, while outside the FoV it increases to 77cm.

Finally, the two-dimensional localization performance with the combination of monopulse function and the

TABLE 2. Angular Errors From Monopulse Estimation.

Zone	RMSE	Mean error	90% percentile
Inside FoV	5.89°	4.66°	9.6°
Outside FoV	40.75°	33.97°	64.9°
Total	27.02°	17.19°	53.38°

TABLE 3. Ranging Errors From RTT Estimation.

Zone	RMSE	Mean error	90% percentile
Inside FoV	71.83 cm	48.47 cm	94.17 cm
Outside FoV	113.67 cm	77.13 cm	169.72 cm
Total	92.1 cm	60.72 cm	128.14 cm

TABLE 4. Euclidean Distance Error From Two-Dimensional Location Estimation.

Zone	RMSE	Mean error	90% percentile
Inside FoV	115.85 cm	94.94 cm	171.47 cm
Outside FoV	446.48 cm	363.6 cm	747.53 cm
Total	304.84 cm	209.82 cm	572.35 cm

ranging measured with RTT is summarized in Table 4 and the associated CDF curves are plotted in Fig.14c. Due to the strong influence of the FoV zone in the AoA estimation, the resulting localization performance also reports a strong degradation outside the FoV, as it can be seen in the corresponding CDF curves in Fig.14c. As summarized in Table 4, 90% of the samples inside the FoV can be localized with 1.7m of error, leading to a mean error below 1 meter inside the vision of the Wi-Fi RADAR. Outside the FoV, the localization error strongly increases above 3.5m, mainly due to the AoA ambiguities. This limited 60° FoV without ambiguities can be increased using beam-scanning monopulse antennas [36], like the one proposed for Bluetooth Low Energy (BLE) localization systems [37].

Therefore, we can conclude that the proposed RTT Wi-Fi monopulse RADAR system provides a mean positioning error below one meter within a Field of View of 60° and distances up to 14 meters. Thanks to the adaptative range-dependent monopulse functions, the localization system can successfully operate also in the near-field zone of the AP, which for Wi-Fi frequencies extends up to 3 meters from the monopulse antennas. Moreover, due to the directly accessible RTT and RSSI data, real-time operation with an acquisition and processing time below 0.5 seconds is demonstrated using a single 802.11mc MIMO Wi-Fi Access Point and FTM-compatible mobile devices. A single commercial AP has been used, without the need of modifying the hardware and/or software to acquire complex CSI / IQ data to obtain Time-of-Flight information. The next Section compares the proposed RTT Wi-Fi monopulse system with other state-of-the-art single-AP Wi-Fi real-time localization systems (RTLs).

V. COMPARISON WITH OTHER SINGLE AP WI-FI RTLs

As depicted in the introduction section, some works about a single-AP localization systems have already been published. As will be detailed below, most of them require complex

processing techniques employing the CSI information or the use of channel hopping mechanism out of the Wi-Fi standard. In the next paragraph and in Table 5, we will describe the information employed in each of the already published single AP system together with the main differences with our system.

CUPID [23] was the first paper published under these premises. Like many other proposals enumerated later, the algorithms require access to the transmission's CSI information. This operation cannot be performed in most of the off-the-shelf AP. Therefore, in the demonstration experiments, the authors do not use a commercial AP. Indeed, they use a laptop with an external Wi-Fi card as an AP, and simulate an IoT device to be localized with another laptop. This is because the system required a modification in the device's PHY layer which is not accessible in commercial smartphones. Moreover, the laptop working as receiver has to run specific tools for accessing the CSI data of the transmission and receive the information of the smartphone's inertial sensors simultaneously. The mean error localization value of this system is around 5 meters.

On the contrary to CUPID [23], the SAIL [24] proposal employed a commercial AP. However, an internal 88MHz WLAN clock is required to compute the Time-of-Flight (ToF) based on Time-of-Departure (ToD) and Time-of-Arrival (ToA) from the PHY layer. This precise clock is not present in commercial Wi-Fi cards. Moreover, the calculation of ToF requires computing the CIR (Channel Impulse Response) from CSI information and the use of dead reckoning system employing the inertial sensor from the smartphone. The reported mean localization error of SAIL is 2.5 meters.

One of the most accurate systems is Chronos [25], with a few decimeters of error in Line-Of-Sight conditions. Chronos implements a channel-hopping mechanism among 35 Wi-Fi channels to estimate the ToF. Since this channel-hopping procedure is out of the Wi-Fi standard, Chronos was implemented into a driver modification and tested with two PCs which must synchronize the frequency band in each hopping with a periodicity of 2-3 msec.

Another channel-hopping proposal is S-Phaser [26]. This system, similar to those above, requires access to CSI information and synchronization algorithms for estimating the distances. The authors proposed a synchronization algorithm for resolving the errors in the phase estimation reading the CSI and computing a precise ranging system, and another algorithm for the ranging estimation. For the testing procedure, a PC was employed to access the CSI information with 1.5 meters of accuracy in Line-Of-Sight (LoS) conditions.

Splicer [28] is another channel hopping approach which integrates a splicing mechanism for aggregating the CSI acquired in different frequencies. This work generated a power delay profile, which was used for computing the ranging to the devices. Some processing techniques are required to remove the amplitude and phase errors introduced by the hardware. The mean error obtained by this works is around 1 meter.

TABLE 5. Comparative Table With Other Single AP Location System.

	Main Characteristics	Problems	Mean Error
Cupid [23]	Ranging and AoA computed accessing the CSI and a inertial sensors from smartphone	The device to locate must have inertial sensors from smartphone.	Around 5 m
Sail [24]	ToF solution employing the CIR from the PHY layer and internal clock of Wi-Fi cards	Needs for a very precise internal Wi-Fi card clock not present in all commercial hardware	2.5 m
Chronos [25]	ToF obtained from CSI with 35 Wi-Fi channel hopping	Requires driver modification out of Wi-Fi standard for channel hopping	Decimeters in LoS
S-Phaser [26]	Ranging system from CSI with two Wi-Fi channels hopping and three MIMO antennas triangulation	Requires driver modification out of Wi-Fi standard for channel hopping	1.5 m in LoS
SiFi [27]	ToF triangulation system based on three MIMO antennas using CSI, and separated from the AP a few meters	Cannot be employed in real-time because the high complexity	0.93 m
Splicer [28]	Power delay profiling with a mechanism for correct the hardware CSI error	Requires driver modification out of Wi-Fi standard for channel hopping	1 m
[29]	Switched Beam Antenna with eight directional antenna	Employs a complex antenna system which must be electronically controlled	0.95 m in anechoic chamber
[30]	Bluetooth RSSI data and motion sensors	The device must have inertial sensors	5.6 m
Proposed method	2D radar with RTT and RSSI-based monopulse antenna	Only cover 60° of FoV	0.95 m

A localization system with a single AP and without channel hopping is SiFi [27]. This work is a ToF one channel system which requires three antennas installed far away from the AP. With the simultaneous access to the CSI from the three antennas, authors can estimate the direct path from the transmitter to each antenna and estimate the delay time. With that information and triangulation, the system achieved an accurate position. The system is tested with a PC with the Linux CSI Tool working as an AP and another PC as the target to localize. The antenna connected to the AP has to be installed several meters away from the PC, and it is a handicap of the system. Additional drawbacks of the system are the high computation complexity which avoids the real-time localization implementation and the limitation of localizing only one user per time. The mean error of SiFi is 0.93 meters.

Similar to our proposal regarding the use of RSSI values without requiring CSI accessing is [29]. However, in this proposal, a complex eight dual 2.4 - 5GHz Switched Beam Antenna designed explicitly for this proposal is required. These antennas must be electronically switched on and off. Our proposal works with RSSI similar to this last one, but on the contrary, only two tiled commercial directive antennas are employed using a commercial 2×2 MIMO Wi-Fi card which can read the RSSI from each titled antenna. Moreover, the mean error reported in [29] is about 1 meter in an anechoic chamber with optimum propagation conditions, and no information is given about its operating real-time performance outside the anechoic chamber. Another RSSI-based single-AP RTLS was proposed in [30]. In this work and similar to [23], [24], because of the limitation of estimating the position employing only a unique AP, a dead reckoning system in the smartphone was implemented using the inertial sensors of the mobile IoT device.

To the authors' knowledge, the proposed RTT Wi-Fi monopulse system is the first single-AP system that can

precisely localize an IoT device without the use of complex signal processing techniques, neither the use of CSI information nor the smartphone inertial system. Only with the use of the RSSI and RTT data directly accessible from commercial 802.11mc MIMO Wi-Fi Access Point, the proposed system is able to estimate the AoA angle and the ranging distance of any 802.11mc-compatible IoT device. With both the angle and the distance, the precise position can be easily determined. Moreover, because of the easy-to-acquire and low-cost complexity, the system is able to localize in real-time and more than one device simultaneously, using a single commercial AP.

VI. CONCLUSION

It has been demonstrated that a single commercial 802.11mc MIMO Wi-Fi Access Point connected to a monopulse antenna, can be successfully used to estimate the Direction-of-Arrival and the ranging distance to a mobile IoT device, without the need of accessing complex CSI data, which relies on non-standard synchronization process (which requests specific hardware and software out of the IEEE WiFi standard to perform the time and/or phase synchronization for precise CSI-based localization). The directly accessible RSSI and RTT information provided by any commercial 802.11mc MIMO Wi-Fi AP is sufficient to perform the two-dimensional localization, thus allowing real-time operation with commercial mobile IoT devices, and without the need of using inertial sensors. It is reported a positioning error below 1 meter, with an acquisition and processing time below 0.5 seconds. Its main drawback is that this succesful performance deteriorates out of the limited monopulse antenna Field of View of 60°, due to angular ambiguities. This limitation can be improved using several APs, or using beam-scanning monopulse systems, at the cost of increasing the overall system complexity. In any case, the demonstrated single-AP real-time

localization performance inside this 60° FoV, together with its relative simplicity, makes this Wi-Fi RTLS an interesting solution for low-cost commercial applications using the 802.11mc FTM protocol for RTT ranging, together with RSSI-based angular monopulse techniques.

In future research we will study the potential localization system improvement when several APs are employed, or when beam-scanning monopulse antennas are used to extend the limited FoV

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Artículo 4

Wi-Fi Direction Finding with Frequency-Scanned Antenna and Channel-Hopping Scheme

Artículo en revision enviado a IEEE Sensors Journal

Wi-Fi Direction Finding with Frequency-Scanned Antenna and Channel-Hopping Scheme

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Abstract— A novel and simple technique for Direction of Arrival (DoA) estimation in 802.11 Wi-Fi networks is proposed. It is based on the use of a dual-port frequency-beam scanning antenna, which is connected to single MIMO access point. By simply performing a channel hopping scheme and acquiring Received Signal Strength Information (RSSI) from each channel, the DoA can be estimated in a wide Field of View of 180° with a mean angular error of 5°. Due to its simplicity, a single commodity Wi-Fi AP can be used without the need of Channel State Information (CSI), or complex electronically reconfigurable or mechanically revolving antennas.

Index Terms— localization with 802.11, direction of arrival (DoA), channel hopping, frequency-scanning antenna.

I. Introduction

DIRECTION FINDING in IEEE 802.11 Wi-Fi Wireless Local Area Networks (WLAN) finds multitude applications for indoor localization, user location tracking, context-aware services, and security [1]–[2]. Besides, in the paradigm of a Smart Home and the Internet of Things (IoT), it is desired that a single Access Point (AP) performs the Wi-Fi sensing and direction finding of mobile devices [1]. In this context, several single-AP Wi-Fi direction finding systems have been proposed in the literature [3]–[12]. Most of them estimate the Direction of Arrival (DoA) with MIMO (Multiple Input Multiple Output) antennas and using Channel State Information (CSI). CSI provides complex data of the received signal, including phase information from which phased-array techniques [5], [7] can be applied to estimate the DoA. However, CSI data is not directly accessible on commodity APs, and ad-hoc hardware and software modification for dedicated synchronization is needed to calibrate the system [6], [8], [9], [12].

On the contrary, Received Signal Strength Information (RSSI) is directly accessible from commercial Wi-Fi APs, and it does not rely on complex time and/or phase synchronization. For this reason, some single-AP Wi-Fi RSSI-based DoA estimation systems have been proposed to avoid the need of CSI

data. When using RSSI (amplitude) data without phase information, a directive beam antenna able to scan the angular space is required to estimate the DoA. One common solution is to use Switched Beam Antennas (SBAs) [4], [10], [13], which require an electronic control circuit to acquire RSSI data from several sectorial antennas, each one scanning at different adjacent angular zones. Also, amplitude-monopulse antennas have been proposed to implement RSSI-based DoA estimation for Wi-Fi [11], [14]. However, since they show a limited Field of View (FoV), more than one AP [11] or a revolving antenna [3], is needed to eliminate ambiguities in wider angular zones. However, both electronically SBAs and mechanically revolved antennas are active-antenna solutions, which increase the cost and complexity of the DoA estimation system since they are not directly integrable with commercial MIMO Wi-Fi AP functionalities.

In this paper, we propose a new RSSI-based direction finding technique for Wi-Fi WLANs, which avoids the use of CSI data, or the need of complex active-scanning beam antennas. The proposed novel technique is based on the use of a simple passive frequency-scanning antenna (FSA), which can be directly connected to a single MIMO Wi-Fi AP without any external control hardware, in order to perform the beam scanning requested for the RSSI-based DoA estimation.

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Fig. 1. Scheme of the frequency-scanned antenna connected to a single MIMO Wi-Fi Access Point performing channel hopping for DoA estimation.

The main novelty of the proposed DoA Wi-Fi technique, is that the beam scanning is based on a sequential channel-hopping scheme, which can be directly performed by commercial APs. As sketched in Fig.1, the FSA antenna can be connected to a single MIMO Wi-Fi AP to produce directive beam scanning over a wide FoV by simply hopping among the available Wi-Fi channels. This is demonstrated in Section II of this paper, which describes the system. Then, the MUSIC technique [15] is applied in Section III to estimate the DoA of Wi-Fi signals in the 2.4 GHz band. It is shown that, by using the 11 available Wi-Fi channels, the DoA can be estimated in a wide Field of View of 180° with a root mean square error of 14° (mean angular error of 5°). Finally, Section IV compares this performance with other single-AP Wi-Fi direction finding systems.

II. SYSTEM DESCRIPTION

Recently it has been proposed a radio direction finding technique using frequency-scanned antennas (FSA) together with multi-tone analog RF signals [16], [17]. This concept was lately applied for DoA estimation in Bluetooth Low Energy (BLE) digital wireless networks [18]. Here we demonstrate its application also for Wi-Fi systems using a similar FSA. For that, a Compex WPJ531HV-A Multi-Function QCA9531 Embedded Board [19] with a mini-PCIe Atheros AR9380 Wireless 3X3 MIMO card is connected to a FSA as shown in the scheme of Fig.1. The FSA has two radio-frequency (RF) ports (port A and port B), which are connected to the two RF interfaces of the MIMO Wi-Fi card. The FSA is similar to the ones used in [16] and [18], but tuned to operate in the Wi-Fi 2.4 GHz band. The main idea is that different Wi-Fi channels are focused to different angular sectors with high spatial directivity, and this can be used to perform directive beam scanning using a simple passive antenna.

To demonstrate this, the system is characterized in an anechoic chamber as shown in Fig.2a. The FSA connected to the Wi-Fi AP is mechanically rotated using a turntable. A mobile device transmits frames using a fixed Wi-Fi frequency channel, and the MIMO AP card measures the RSSI levels for different azimuthal angles ϕ as it is being rotated. In this way, the digital radiation patterns are obtained for different Wi-Fi channels (from #1 to #11), and for the two RF ports (A and B). The normalized patterns are shown in Fig.2b, demonstrating the successful generation of directive beams, which are digitally steered by just sweeping the selected Wi-Fi channel.

Fig. 2. a) Experimental setup in anechoic chamber b) Measured digital beam patterns in Wi-Fi channels #1, #6 and #11.

As it can be seen in Fig.2b, Wi-Fi channel #1 (with central frequency 2.412 GHz) is received in port B with a directive sectorial beam directed at $\phi \approx +20^\circ$. As the Wi-Fi channel is increased, the beam direction is steered to higher scanning angles ($\phi \approx +30^\circ$ for channel #6 with 2.437 GHz, and $\phi \approx +40^\circ$ for ch.#11 with 2.462 GHz). The rest of the beams associated to all 11 Wi-Fi channels are not plotted for the sake of clarity; however they show a smooth continuous scanning response of their peak gain direction from $\phi \approx +20^\circ$ to $\phi \approx +40^\circ$. Similarly, channel-scanning to negative angles ϕ is performed when acquiring Wi-Fi frames from port A of the MIMO Wi-Fi card, due to the mirror-symmetric electromagnetic response of the FSA [16].

As it was mentioned in the introduction, directive beam scanning or beam switching among different directions is necessary to perform DoA estimation using only amplitude information (RSSI), thus avoiding the need of complex CSI data for phase acquisition. Obviously, the frequency-beam steering technique demonstrated in Fig.2b, provides simpler angular scanning mechanism than electronically switched-beam antennas [4], [10], [13] or mechanically rotating antennas [3], which request for active external hardware to perform the beam scanning or the sectorial beam switching.

When the two ports of the MIMO Wi-Fi AP and the 11 Wi-Fi channels are combined together, a total of 22 directive scanned beams are obtained. The resulting overall digital Wi-Fi channel-hopping scanning response is plotted in Fig.3a with 22 red circles, each one corresponding to the direction of maximum Wi-Fi RSSI level, produced by each one of the 22 scanned beams. This digital Wi-Fi response is compared with the analog frequency-scanning curve of the FSA, which is shown with dashed black line in Fig.3a. The analog scanning response is obtained using a microwave Vector Network Analyzer (VNA) connected to the FSA, and measuring the associated analog radiation patterns.

Fig. 3. Characterization of a) maximum radiation angle and b) beam peak gain.

The measured Wi-Fi digital scanning response is consistent with the expected analog microwave response of the FSA plotted in Fig.3a. The small discrepancies observed between them are due to the fact that the Wi-Fi patterns are measured using the RSSI of Wi-Fi digital frames modulated using a 20 MHz bandwidth, while the analog results are obtained using pure RF tones generated by a microwave VNA and acquiring analog power levels. These obvious differences between the analog and the digital Wi-Fi measurements, produce a small shift in the beam scanning responses. In any case, it is the digital response the one that needs to be considered for the DoA estimation using Wi-Fi signals and the MUSIC algorithm, as it will be explained in the next paragraphs.

Similarly, the peak gain of the beams as they are frequency-scanned in space, must be characterized to calibrate the Wi-Fi system response in the digital domain. Certainly, the 22 obtained beams can show different peak power levels for the different scanning directions. The measured Wi-Fi peak RSSI levels (dBm) obtained in the anechoic chamber for each beam, are shown in Fig.3b with red circles. It is corroborated that the peak power response is not uniform, showing a maximum RSSI level of -47.5 dBm for beam B7 (port B and channel#7, pointing at $\phi \approx +30^\circ$), while beam B1 directed at $\phi \approx +20^\circ$ shows the minimum RSSI level of -50.5 dBm. This digital power response can be attributed to several factors. First, it is due to the fact that the FSA has an analog RF peak gain response which is not constant as the beams are scanned [16]. This analog gain response (in dBi) is plotted in Fig.3b with dashed black line, showing that the beam peak gain decreases close to the

perpendicular angles (beams A1 and B1 with 6.6 dBi), and also for beams scanning towards most side angles (beams A11 and B11 with 6 dBi), being the central beams the ones with highest gain (beams A4 and B4 with 7.4 dBi). This fluctuating behavior can be also recognized in the digital gain response. Therefore, it is the varying analog gain of the FSA antenna as it scans with frequency, the main responsible for the digital RSSI non-uniform peak gain response as the Wi-Fi channel is varied. Also, it can be observed that the digital peak gains obtained in port A (negative scanning angles) and port B (positive scanning angles) are not completely symmetrical. For instance, beam B7 shows the maximum RSSI level of -47.5 dBm, while its mirrored counterpart beam A7 shows a lower RSSI of -47.8 dBm. This difference must be due to the electronics of the Wi-Fi MIMO card when measuring RSSI levels from port A or port B. In any case, the digital Wi-Fi RSSI gain response for all 22 beams must be calibrated to construct the MUSIC steering vectors as described next.

The MUSIC (Multiple Signal Classification) algorithm [15] has been extensively applied to estimate the DoA in Wi-Fi using multiple antennas (normally three), and phase-shift information obtained from CSI data [5]-[8]. Mathematically, the MUSIC angular pseudo-spectrum $P(\phi)$ is constructed with the following equation:

$$P_{MU}(\phi) = \frac{1}{a(\phi)^H E_N E_N^H a(\phi)} \quad (1)$$

where $a(\phi)$ are the so-called MUSIC steering vectors, H denotes the Hermitian, and E_N is a matrix whose columns are the eigenvectors of the music matrix. As commented, previous single-AP Wi-Fi DoA estimation systems use phase-shift information between the different antennas of the MIMO AP, in order to construct the steering vectors for different bearing angles ϕ . In our case, we use amplitude information (RSSI data) from each one of the 22 available scanned beams to construct the RSSI-based steering vectors:

$$a(\phi) = [RSSI_1(\phi), RSSI_2(\phi), \dots, RSSI_n(\phi)] \quad (2)$$

with $n=1..N=22$. As an example, the steering vectors for three illustrative directions $\phi=-60^\circ$, $\phi=0^\circ$, and $\phi=+60^\circ$ are represented in Fig.4. As it can be seen, they are vectors with 22 elements, corresponding to the RSSI levels acquired at each of the 22 directives scanned beams. Once the RSSI levels are normalized using the digital peak gains in Fig.3b, and when these RSSI levels are arranged from channel A#11 to channel B#11, the shape of the calibrated steering vectors have a geometrical interpretation which can directly be connected to the DoA, as explained next.

When a Wi-Fi signal comes perpendicularly to the FSA, the associated steering vector presents a RSSI profile with a power distribution showing a maximum of received signal for central channels (A1 and B1, which correspond to the beams pointing at this perpendicular direction $\phi=0^\circ$), as it is shown in Fig.4b. As the DoA of the Wi-Fi signal moves to the left direction (negative angles), the RSSI peak shifts to left channels as shown in Fig.4a for a Wi-Fi signal coming from $\phi=-60^\circ$.

Fig. 4. Calibrated MUSIC steering vectors at three illustrative bearing angles: a) $\phi = -60^\circ$ b) $\phi = 0^\circ$ and c) $\phi = +60^\circ$.

As shown in Fig.4a, in this case the maximum received power level corresponds to channel A11, whose associated beam points at $\phi = -40^\circ$ and thus receives higher RSSI than the rest of the beams. Conversely, if the Wi-Fi signals move to right (positive) angles, the RSSI peak of the associated steering vector moves to the right channels. This is illustrated in Fig.4c for a Wi-Fi signal coming from $\phi = +60^\circ$, showing a steering vector with a power profile distribution with maximum RSSI at channel B11 (which corresponds to the beam pointing at $\phi = +40^\circ$). Therefore, the RSSI profile associated to the calibrated steering vectors can be geometrically connected to the angular quadrant where the signal comes from. This rough qualitative interpretation is given for the sake of simplicity. Obviously the quantitative accurate estimation of the DoA is performed by applying the MUSIC mathematical formulation, which uses the calibrated steering vectors (2), to compute the angular pseudo-spectrum (1), as it will be shown next.

In this context, it must be clarified that although the direction of maximum radiation of the scanned beams shown in Fig.3a, is steered from $\phi \approx -40^\circ$ to $\phi \approx -20^\circ$ and from $\phi \approx +20^\circ$ to $\phi \approx +40^\circ$, this does not mean that the system cannot estimate the DoA out from this limited angular zone. Certainly, the radiation patterns in Fig.2b show a half-power beam width (HPBW) of approximately 30° . As a result, when considering the whole 22 beams angular coverage, any Wi-Fi signal coming from all possible angular directions covering the wide FoV from $\phi = -90^\circ$ to $\phi = +90^\circ$ can be detected, and its DoA estimated.

Fig. 5. MUSIC angular pseudo-spectrums $P(\phi)$ obtained for different DoA directions: a) DoA = -60° b) DoA = 0° and c) DoA = $+60^\circ$.

For instance, the three steering vectors shown in Fig.4 correspond to Wi-Fi signals coming from directions $\phi = -60^\circ$, $\phi = 0^\circ$ and $\phi = +60^\circ$. Although these directions are out from the peak gain scanning curves in Fig.3a (from $\phi \approx \pm 20^\circ$ to $\phi \approx \pm 40^\circ$), the MUSIC algorithm can resolve the associated DoA since the information of the calibrated steering vectors capture the variation of the RSSI for *all* possible directions in a wide FoV of 180° .

This is demonstrated by computing the MUSIC angular pseudo-spectrums $P(\phi)$ (2) for the aforementioned studied DoA $\phi = -60^\circ$, $\phi = 0^\circ$ and $\phi = +60^\circ$. They are shown in Fig.5. The MUSIC angular pseudo-spectrum must present a peak at the actual DoA of any arriving Wi-Fi signal. This is demonstrated in Fig.5 for the studied directions. As commented, this is true even for signals coming out from the scanning region of the FSA. For instance, the spectrum shown in Fig.5a for a Wi-Fi signal coming from the direction $\phi = -60^\circ$, shows a clear unique peak at the real DoA. The same happens for directions $\phi = 0^\circ$ and $\phi = +60^\circ$ in Fig.5b and Fig.5c, respectively. Similar successful DoA estimations were achieved for all directions in the wide angular region of 180° . It must be highlighted that the results in Fig.5 were obtained in ideal static conditions inside the anechoic chamber, where the same Wi-Fi direction-finding system was calibrated. In the next Section, the DoA estimation performance is evaluated in a dynamic outdoor environment.

III. WI-FI DOA ESTIMATION PERFORMANCE

Fig. 6. a) Scheme and b) Picture of the experimental set-up outside the anechoic chamber.

Once the digital Wi-Fi MUSIC steering vectors have been calibrated in the anechoic chamber in static conditions, the single-AP Wi-Fi system is evaluated in an outdoor scenario. The scheme of the outdoor experimental setup is represented in Fig.6. The FSA connected to the MIMO Wi-Fi AP is mounted on a tripod in front of a wall. A Wi-Fi compatible mobile device connects to the AP SSID, which dictates the channel frequency. The mobile device is located at different angular points in a semi-circumference with a radius of 3 meters from the AP. For each angular position, the DoA is estimated by acquiring the RSSI levels as the AP performs the channel-hopping scheme, which is followed by the mobile terminal to refresh the active Wi-Fi channel. Then, the estimated DoA will be compared to the real bearing angle.

The dynamic nature of the Wi-Fi channel hopping plays an important role in the DoA estimation performance. Certainly, the DoA system must be able to scan the full 180° angular space as fast as possible, so to determine the DoA with minimum delay for real-time applications. For that, the Wi-Fi AP must perform the channel-hopping dynamically and acquire the RSSI levels of the incoming Wi-Fi signals for all frequency channels. The channel-hopping technique has been used in other single-AP Wi-Fi DoA systems such as Chronos [20] or S-Phaser [21].

As an example of this dynamic channel-hopping RSSI acquisition, Fig.7 shows the RSSI data recorded when switching between three different Wi-Fi channels #1, #6 and #11. The Wi-Fi AP configures its operating channel every 100 msecs., and then hops to the next channel. The Wi-Fi frames are sampled each msec., so that 100 RSSI data are recorded per channel. As it can be seen in Fig.7, the RSSI levels are not stable in time. Particularly, the RSSI varies during the first 20 msecs. after the AP has switched from one channel to the next one. After this time, the RSSI level shows a more stable mean value with sudden peaks which might be due to interferences or multipath effects. These stronger variations of the acquired RSSI levels observed in the first 20 msecs., might be due to the mobile device which needs this time to follow the channel hop dictated by the Wi-Fi AP. In any case, it is shown that it is needed to keep this 20 msec. preamble for each channel hop, and thus skip the first 20 RSSI samples for a more stable RSSI signal.

Fig. 7. RSSI acquired from Wi-Fi signals using channel-hopping scheme.

Under these dynamic channel-hopping conditions, the single-AP Wi-Fi direction finding performance is evaluated by estimating the DoA for different angles in a wide 180° FoV. For that, the mobile device is connected to the AP at a distance of 3 meters following the scheme in Fig.6, and the AP executes a sequential channel-hopping scheme over a set of N channels. The mobile device follows the connection at the channel sequentially dictated by the MIMO AP, which measures the RSSI levels acquired by each port of the FSA. As commented, the connection is held in each Wi-Fi channel for 0.1 secs, and a total of 100 RSSI samples per channel are acquired during this time. The RSSI values for each channel are averaged, and once the RSSI from the N Wi-Fi channels have been acquired, the MUSIC technique is applied to estimate the DoA. The process is repeated for all testing angles from $\phi = -90^\circ$ to $\phi = +90^\circ$, and the root mean square error (RMSE) between the real bearing angle and the estimated DoA is evaluated.

In Fig.8 it is shown the distribution of the RMSE in the DoA estimation for all testing angles, as a function of the number of Wi-Fi channels N used in the channel-hopping technique. First, Fig.8a shows the results when using $N=3$ Wi-Fi channels (namely #1, #6, and #11). The DoA estimation error is lower when the Wi-Fi signal comes from angles close to the perpendicular direction of the antenna ($\phi=0^\circ$), showing a RMSE below 20° in this central zone. The error increases up to 30° RMSE as the bearing angle approaches $\phi=\pm 60^\circ$. This better performance for perpendicular DoA directions is due to the richest angular diversity provided by the FSA directive beams at these directions, which leads to more angle-sensitive steering vectors for $\phi=0^\circ$ than for higher angles $\phi=60^\circ$, as it was shown in Fig.4. Also, it is plotted the effect of skipping the first 20 samples to avoid variations in the preamble of each channel switch, showing that the angular error slightly decreases as expected.

Similar angular distributions of the DoA RMSE are obtained when the amount of used Wi-Fi channels is increased to $N=6$ in Fig.8b (namely #1, #3, #5, #7, and #11). The RMSE in the central angular zone has decreased below 15° , while for angles in the $\phi=\pm 60^\circ$ zones the RMSE keeps higher around 30° . When all $N=11$ Wi-Fi channels are used, Fig.8c reports a reduction of the RMSE below 10° in the perpendicular direction of the antenna, and below 25° in the side directions.

Fig. 8. Angular distribution of the RMSE for the DoA estimation using different amounts of Wi-Fi channels N: a) N=3 a) N=6 and c) All N=11.

Therefore, despite the amount of Wi-Fi channels being used, the DoA error is lower around the perpendicular direction of the antenna, and the 20 msec. preamble decreases the angular estimation error.

In any case, it is patent from Fig.8 the positive effect of increasing the number of Wi-Fi channels N , which decreases the RMSE for all observation angles in the wide FoV of 180° . Obviously, the MUSIC algorithm benefits from a larger number of independent elements in the steering vectors, in order to resolve the angular space with higher accuracy [15]. As N is increased, the length of the steering vectors (2) increases to $(2*N)$, which is the amount of associated scanned beams. Therefore, a higher amount of used channels improves the angular sensitivity and thus the ability to distinguish between different DoA, since more directive beams are used to sniff the angular space.

To better illustrate this improvement, the DoA RMSE as a function of the evaluated FoV is represented in Fig.9, when using $N=3$, 6 and 11 channels, and comparing the use of the 20 msec. preamble. The FoV is defined as the angular region from the perpendicular direction of the antenna (for instance, a $\text{FoV}=30^\circ$ means that the RMSE has been evaluated from $\phi=-15^\circ$ to $\phi=+15^\circ$). As the FoV widens from the perpendicular direction of the antenna, the angular RMSE in Fig.9 increases despite the number of used Wi-Fi channels N , as it was demonstrated in Fig.8. Also in any case, this preamble improves the DoA estimation performance by reducing the RMSE in two degrees approximately, independently of the number of used channels N and the evaluated FoV. Similarly, when the number of Wi-Fi channels N is doubled, the RMSE in the DoA estimation is reduced in an amount of four degrees and for any evaluated FoV

Fig. 9. RMSE for the DoA estimation as a function of the Field of View, and for different amounts of Wi-Fi channels N

These results are summarized in Table I. It must also be considered that when the number of Wi-Fi channels used in the channel-hopping scheme is increased, the RSSI acquisition time rises. In our example, each extra frequency channel used needs 0.1 sec to acquire 80 RSSI samples per channel, which are averaged to eliminate the effects of RSSI peaks observed in Fig.6. Thus, 1.1 secs. Are needed to perform the channel hopping through all the $N=11$ Wi-Fi channels, and to obtain the best DoA estimation performance. The acquisition and processing time is negligible. Therefore, it can be concluded that 1.1 secs are needed to make an angular estimation with the highest accuracy. If less channels are used, this acquisition time can be reduced. Table I also represents the estimation time requested as a function of the used number of channels N .

Also, it is clear from Fig.9 that, as we increase the operational FoV from the perpendicular direction of the antenna, the overall DoA estimation performance degrades showing a higher RMSE. The FoV determines the total angular range for DoA estimation, and this depends on the application in the context of Wi-Fi sensing in Smart Homes [1]. Two illustrative cases are highlighted in Table I. If the Wi-Fi AP is located at the corner of rectangular rooms, a FoV of 90° is enough, and the proposed system reports a DoA estimation RMSE below 10° (with $N=11$ channels) for this case of use. Conversely, if the AP is located on the ceiling or on a plane wall, it might be necessary to cover a complete semi-circular FoV of 180° , reporting a higher RMSE of 14° in the DoA estimation.

Therefore, depending on the FoV to be observed (which depends on the topology and location of the Wi-Fi AP), and depending on the requested angular accuracy and delay response, one might choose a channel-hopping scheme using a different amount of Wi-Fi channels N

In the following section, the performance of the proposed direction finding technique using Wi-Fi signals, is compared to other single-AP Wi-Fi DoA estimation systems which have been reported in the published literature.

TABLE I
RMSE IN THE DOA ESTIMATION AS A FUNCTION OF FIELD OF VIEW (FOV)
AND FOR DIFFERENT AMOUNTS OF WI-FI CHANNELS N
(WITH 20 MSEC PREAMBLE)

FoV	N = 3	N = 6	N = 11
45°	14.1 °	10.5 °	7.1 °
60 °	16.3 °	13.3 °	7.9 °
90°	18.0 °	14.8 °	9.9 °
120°	19.6 °	16.9 °	12.7 °
180°	21.7 °	18.4 °	14.0 °
Processing time	0.3 secs.	0.6 secs.	1.1 secs.

IV. COMPARISON WITH SINGLE-AP WI-FI DOA SYSTEMS

Table II compares the performance of different single-AP WiFi DoA estimation systems which can be found in the literature. They have been grouped according to the technique used for the DoA estimation. First, it can be found many systems which apply phased-array techniques using the phase delay between multiple (typically three) antennas of MIMO Wi-Fi APs [5], [7], [12]. However, the phase delay is not directly accessible in commercial Wi-Fi AP, and dedicated FPGA [5], and hardware modification for phase-calibration is requested for high-fidelity array signal processing [7], [12].

The best performance is reported by the recent OpArray system [12], with a median error of 9° in the DoA estimation and for a 180° FoV. In the second group, Wi-Fi Channel State Information (CSI) is acquired to derive the phase-delay between antennas of a MIMO Wi-Fi AP, reporting a median DoA estimation accuracy between 20° [6] and 10° [8]. In any case, these methods are not directly realizable in commercial Wi-Fi APs, since they need precise clock calibration for accurate phase estimation from CSI data. On the contrary, RSSI is directly available from WiFi AP without the need of hardware/software modifications and phase corrections.

For this reason, RSSI-based DoA estimation techniques are of much interest for low-cost Wi-Fi single-AP localization. The first proposal was VORBA [3], which used a mechanically revolving directive antenna to acquire the RSSI from different directions, reporting a DoA estimation with a standard deviation of 22°. Its main drawbacks are the need of a mechanical steering mechanism to cover a FoV of 360°, which requires a turn-period of approximately 2 secs. Electronic scanning can be obtained by using Switched Beam Antennas (SBA), as proposed for RSSI-based DoA estimation with Wi-Fi AP in [4], [10], [13]. The SBA Wi-Fi direction finding system in [10] reports the best DoA performance with a mean error of 7.1° in a 360° FoV. The 8-element dual-band SBA system is complex, requiring electronic control circuitry to perform the switching between the 8 sectorial antennas. Much simpler is the RSSI-based WiFi DoA monopulse technique which uses only two fixed tilted panel antennas [11], [14], thus avoiding complex antenna systems for mechanical or electronic beam scanning. Its main drawback is that the FoV is limited to 60°, reporting a RMSE in the DoA below 5°. Therefore, all previous single-AP Wi-Fi RSSI-based DoA techniques need some sort of electronic system to scan the directive beams in a wide angular FoV.

TABLE II
SINGLE-AP WI-FI DOA PERFORMANCE.

System	DoA estimation Technique	FoV	DoA mean error
ArrayTrack [5] Phaser [7] OpArray [12]	Phased-array using phase information from dedicated and calibrated hardware	180°	[12] 9 °
CUPID [6] SpotFi [8]	CSI to derive phase-delay between MIMO AP antennas	180°	[6] 20 ° [8] 10°
VORBA [3]	Mechanically revolving antenna	360°	[3] 22°
SBA [4] [10] [13]	Electronically-controlled Switched Beam Antenna	360°	[10] 7.1°
Monopulse [11] [14]	RSSI-based Monopulse with two panel antennas	60°	[14] 4.3°
This work	FSA connected to WiFi AP	180°	5.4°
FSA in BLE [18]	Array of two FSA connected to four BLE beacons for RSSI DoD	120°	3.7°

As it has been demonstrated, the system proposed in this work uses a Frequency-Beam Scanned Antenna tuned to the Wi-Fi channels, to directly provide 22 beams which scan the 180° FoV angular space by simply performing channel hopping. In this way, simple RSSI-based DoA estimation techniques can be applied without the need of mechanically or electronically scanning antennas, which request extra control hardware. We report a mean error of 5.4° when using the N=11 Wi-Fi channels (RMSE of 14°), which is comparable or better to previous reported performances, and without the need of CSI data acquisition for phase-shift DoA processing, which is out from the Wi-Fi standard.

Finally, the performance of the proposed single-AP WiFi DoA estimation is compared with the similar FSA technique applied for BLE (Bluetooth Low Energy) in [18]. There, it was reported an angular RMSE of only 3.7° for a FoV of 120°, sensibly better than the RMSE of 12.7° reported here for a similar FoV. The reason for this better performance in BLE when compared to the proposed Wi-Fi can be attributed mainly to the much more stable power transmission of BLE beacons, which didn't show the RSSI variations observed in the received Wi-Fi power levels in Fig.6. Actually, BLE beacons are IoT devices dedicated indeed to serve as stable signal transmitter, and they automatically implement the channel-hopping scheme between three advertising channels to optimize the distance and DoD (Direction of Departure) estimation. All this makes the channel-scanning RSSI-based DoA technique to be more robust with BLE beacons than with Wi-Fi frames.

V. CONCLUSION

It has been demonstrated that a Frequency-Scanning Antenna (FSA) can be connected to a MIMO Wi-Fi AP to estimate the DoA of Wi-Fi signals. For that, the AP performs a sequential channel-hopping scheme on the 11 available Wi-Fi channels, and acquires the RSSI levels associated to 22 directive beams which scan the angular space.

The MUSIC method has been applied, reporting a mean error of 5.4 deg (RMSE of 14°) in wide FoV of 180°, which is competitive with current state-of-the-art single-AP Wi-Fi DoA systems. The system time response for data acquisition and angular estimation is 1.1 secs.

The proposed solution has two main advantages. First, it is based on RSSI data which is directly accessible from commercial APs, if compared to CSI-based DoA systems which require precise phase and/or time synchronization out of the Wi-Fi standard. Second, the antenna is completely passive and performs the beam scanning for RSSI-based DoA estimation, without the need of electronically switched-beam or mechanically rotating antennas. As a result, it has been demonstrated a simple RSSI-based DoA estimation technique for low-cost single-AP Wi-Fi systems.

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Artículo 5

Evaluation of an indoor positioning system for added-value services in a mall

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Evaluation of an indoor positioning system for added-value services in a mall

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Abstract— We present a Wi-Fi smartphone active shop-level Indoor Location System stable over time, which can generate a business model for an IT company. The proposed system covers all the steps in the deployment of the solution, from the digital map creation to the evaluation of the performance. To avoid unnecessary battery drain, only RSSI levels of already deployed Access Point are used in the location algorithm. The system has been deeply tested against several smartphones with a suitable accuracy in a medium-size mall, independently of the occupancy level and the smartphone model employed in the validation routes.

Keywords—Indoor location system, smartphone location, Wi-Fi fingerprint, recommender service, mall.

I. INTRODUCTION

There is an increased interest in giving an improved in-store experience, based on the visitors' behavior and needs. In particular, there can be an improvement of the client experience at a mall by means of a recommender service through a smartphone app with custom and personalized content [1]. A recommender service depends on the position context and, at least, it is needed a shop level resolution as a requirement for the indoor location service at the mall.

In order to push a new business model for an IT company, in this paper it is considered a shop-level indoor location service which minimizes the TCO (Total Cost of Ownership), without installing new hardware nor infrastructure, and, at the same time, easing all the operational phase, including the installation and set-up process.

Wi-Fi is one of the most used technologies on indoor location systems (ILS) [2] at retail, malls, airports, hospitals, museums, etcetera. The growth of the Wi-Fi has been caused by the demand for connectivity from the visitors, who usually carry a smartphone. Nowadays, Wi-Fi infrastructure is densely deployed in any mall.

Within the subset of ILS using Wi-Fi signals, the fingerprint technique based on RSSI (Received Signal Strength Indicator) is the most widely used on Wi-Fi indoor positioning systems. The Wi-Fi fingerprint method can be classified into two different groups depending on the way to acquire the RSSI data [2], [3]. If the smartphone itself collects the RSSI data from the beacons transmitted by the surrounded AP (Access Points) to generate the fingerprint, it is called an active system. On the other hand, if an infrastructure of Wi-Fi sniffers has to be installed to collect the RSSI data from the transmitted traffic from surrounding smartphones, the system is referred to as passive. Passive methods require the

installation of a high number of specially designed devices – the sniffers –, thus needing a more costly operational start-up in large areas.

In the literature, several active Wi-Fi smartphone ILS can be found using inertial and magnetic sensors to detect relative movement [4]. The information generated with these sensors is merged with RSSI fingerprinting technique. This system achieves a high precision level at the expenses of heavy use of the smartphone battery. However, in the case of the system to be used over extended intervals of time as the proposed one, only fingerprinting RSSI system is recommended to keep the large operational time of the user's smartphones. Creating an ILS for a large indoor area using only this RSSI input depends primarily on following the factors: density of APs, heterogeneity of the smartphone [5], the variability of the occupation [6], and the change on the radio map because APs disappear and emerge [7].

Bearing in mind these premises, we study the performance of an active Wi-Fi fingerprinting system, intended for shop-level smartphone ILS in a large mall area. The system has been extensively evaluated, showing that it can handle hardware heterogeneity, it works accurately independently of the people occupancy, and its performance is stable over time.

In order to evaluate the ILS performance, a digital map has been built where each shop/corridor is considered a node located at a centroid reference point. For every smartphone RSSI labeled sample acquired in the evaluation route, the ILS estimates a zone (a shop which corresponds to a node in the digital map). In this way, the Euclidean distance between nodes (between the real location shop and the estimated shop) can be computed to estimate the location accuracy as a performance metric. A recommender service needs to be as close as possible to the real shop to work correctly. Due to that, the system tries to minimize the mean error distance of all labeled samples for the whole area, adapting to the available Wi-Fi infrastructure and dealing with smartphone hardware heterogeneity and different movement patterns from people.

The paper is organized as follows. Section II summarizes the state-of-the-art in smartphones fingerprinting ILS. A complete description of the proposed Wi-Fi ILS is explained in Section III. The test scenario is described in section IV, detailing the mall area, the type of smartphones used, and the validation routes which have been evaluated under different circumstances. Finally, Section V reports the results of the performance of the system.

II. RELATED WORK

In the literature, several methods to infer locations based on the analysis of radio signals can be found. Depending on the problem to tackle, these solutions have specific requirements like the type of needed measurements, the scanning period, and the parameters extracted from radio signals which must be analyzed. The most common radio technology is the Wi-Fi 802.11, though others like Bluetooth, RFID or ZigBee also have their application niche.

Related to those methods based on the analysis of radio signals, we emphasize the importance of the network scanning process, which can be categorized in the following two different approaches: active scanning or passive scanning. In the active scanning technique, a mobile device examines each available frequency channel waiting for either incoming frames generated by other devices. Depending on the used network card and the OS (Operating System) specifications at smartphones, authors of [8] empirically studied the values used by several wireless network card manufacturers concluding that an active scan of all channels (considering the 13 Wi-Fi channels at 2,4 GHz available in Europe) takes around 300 milliseconds to complete.

On the other hand, passive scanning was introduced to reduce the workload of mobile devices and hence to save battery power. As indicated by its name, passive scanning does not require any active communication of the mobile device. During the process, a device listens to each channel and waits for a given period of time. If an AP is assigned to a particular channel, the mobile station should receive a so-called Beacon frame. Every AP broadcasts Beacon frame on a regular basis (usually every 100 milliseconds) to maintain the network. By examining the received frame, a mobile device is able to recognize neighboring APs and their capabilities. Once again, note that this configurable value is not defined by the IEEE 802.11 standard. In total, a passive scan requires at least 1.3 seconds to be completed. This is nearly five times the time required for an active scan mode. The main disadvantage of this type of proposals is the difficulty of managing the network infrastructure in those scenarios in which the location system has to be deployed.

Focusing on 802.11 approaches, we can start mentioning those based on lateration methods, which estimate the position of an object by measuring its distances from multiple reference points. That is the case of the time-of-arrival (TOA) [9], [10] and the time-difference-of-arrival (TDOA) [11], [12] methods, which estimate the positions from distance-related measurements to fixed sensors (emitters or access points) with known positions. Despite the excellent accuracy that can be obtained with estimations of less than one meter of error, these time-based methods require particular sensors or hardware to be installed in the covered area due to the requirement of precise synchronization. Though this drawback is alleviated in TDOA, the accuracy is still limited because of inherent multipath fading and non-line-of-sight (NLOS) propagation factors which appear in indoor environments.

Related to previous techniques, Angle-of-arrival (AOA) methods work by observing the angle of arrival of signals. The location of the mobile device can be estimated by the intersection of several pairs of angle direction lines [13]. However, to obtain accurate estimations, the collection of precise measurements is required. For that purpose, an alternative is the utilization of directional antennas or antenna

arrays, as proposed in [14]. Nevertheless, despite the high accuracy, it notably increases the cost of the system. As in the previous case, AOA methods work well in line-of-sight (LOS) situations but are susceptible to multipath interference, thus accuracy and precision decrease when confronted with signal reflections from surrounding objects typically present at indoor scenarios.

In general, most of the affordable alternatives, from the point of view of usability and scalability, are those based on the analysis of the RSSI, which can be classified within two general categories: radio-frequency (RF) ranging methods, and fingerprinting methods. RF ranging-based methods utilize signal theory to define propagation models that estimate the distance between a wireless device and the observed access points. This type of methods is frequently classified as a particular type of lateration approach, which can also be performed by using RSS, based on the knowledge of the transmitter output power, the antenna gain, and the appropriate path loss model. The complexity of signal propagation in indoor environments has been analyzed in [15] and [16]. The main difficulties derive from the complexity of extracting the attenuation factor that influences the RSS transmissions. Hence, these methods can be considered as empirical approaches since they do not make any assumption about the environment or signal propagation paths.

On the other hand, systems based on fingerprinting work in two phases, an off-line or training phase is performed to build a labeled map of radio signals (the radio map) of the environments. Then, it is during the on-line phase when the system is ready to estimate the user location.

One of the imposed requirements of every location-based system is the support of heterogeneous hardware clients. Homogeneous radio maps can be built from RSS data collected with a single device or by several contributors carrying the same devices. Alternatively, in [17], a clustering algorithm to similar group devices in clusters is presented so that they can share the fingerprints among them. In the same way, the authors of [18] addressed the heterogeneity of devices by considering signal-strength ratios between pairs of base stations instead of absolute signal strengths, demonstrating the benefits of these techniques obtaining similar results to those using a manual calibration. A more modern alternative and the one we focus on analyzing deeply in the rest of the paper is the FreeLoc algorithm [19], which addresses the heterogeneity of the devices estimating their positions based on the relative order of the received signal strength. We had the opportunity of testing this technique obtaining good results in terms of feasibility using a coarse-grained grid layout. This proposal seems to be appropriate for those cases in which obtaining a high accuracy is not a necessary requirement, and it is not possible to carry out an exhaustive training. In those scenarios in which the accuracy is not the main requirement but the capacity of estimating the presence and the rough movements of the users, like inside large buildings such as malls, airports or hospitals, among others. In that sense, systems reaching a zonal/room/shop accuracy can be kind enough to allow an appropriate analysis of user behavior.

More in relation to the type of scenarios where we have focused our research, we could find several proposals working in the same field. We want to highlight the COEX example [20], that was the first mall with indoor location and navigation RSSI based service deployed. Another work also

tested in big malls was [21], where authors proposed a customized ILS tackling the heterogeneous mobile device problem in large buildings. Another interesting work is [22] that shows a comparative evaluation of several indoor positioning techniques set at a large building. Taking as a reference all these works, we carry out an in-depth study trying to build a solution able to provide appropriate service in terms of accuracy, scalability, reliability, managing device heterogeneity and offering an easy-to-deploy service.

III. SYSTEM ARCHITECTURE

The proposed indoor location system must have reduced manpower labor and achieved suitable performance and accuracy to allow real deployments for an IT company. Therefore, it must be efficient in all the steps, from engineering to set-up and maint, enhance costs, since the goal is a scalable system that could be implemented in a multitude of infrastructures/buildings with a proportionate effort. Usually, to build an ILS such as the proposed, one has to follow these phases [20]: 1- indoor digital map creation, 2- Wi-Fi radio map acquisition/fingerprint creation, 3- system build-up, and 4- testing/launching. The approaches chosen in each phase are described afterward.

A. Digital map creation

Keeping in mind the goal of a shop-level indoor positioning classification for multiple buildings –it is not required a high precision path dead-reckoning, or indoor navigation system–, a simple but effective zone-level indoor map creation should be addressed. For that purpose, the open-source Jinedit [22] tool created by the Spatio-Temporal Databases Laboratory from Pusan National University of South-Korea, has been slightly modified. The Jinedit tool is based on the indoor GML standard, which defines several models and syntaxis for building indoor digital maps [23].

The first step for the digital map creation starts with a text-plain file with the code and the name of each shop/corridor and a scale indoor image of each floor. Each shop/corridor will match with a zone of the ILS and using Jinedit the centroid of the zone is selected as a *state*. The possible walking path between two states is considered a *transition*. Moreover, the stairs, elevator as well as other zones interconnection are modeled with *transitions* between *states*. With these considerations, the matrix of Euclidean distance and the walking distance from one zone to any other one can be calculated. At the moment, only the Euclidean distance between zones is employed in the system as an error metric between the estimated zone by the indoor-location algorithm and the real zone of the adequately labeled test sample. In further works, the walking distance should be used for the implementation of person movement models. This complete information about zones, transition, and distances between zones is stored in a database, employed later in the subsequent phases. Fig. 1 reproduce the digital map creation phase of the real medium-size mall under study, from a 2D layout with shops and corridors, defining the centroids of each zone and the connections between them. As a size reference, a circle covering a 30 meter-radius distance is superimposed.

Fig. 1. Illustration of the use of Jinedit and distance of 30 meters in a medium size mall where the system has been tested.

B. Wi-Fi radio map acquisition

One of the essential targets of this work is the creation of an affordable system that works for a long time. One of the most laborious tasks in the deployment of an ILS is the off-line calibration phase. In a large area such as proposed, the calibration should be carried out cost-effectively during the least time possible while acquiring a reliable fingerprinting that should last employable over a long time. With the target of distributing the system effortlessly to various different malls, and without specialized workforce required neither specific hardware, we employ a **random walking survey** method. For the radio-map acquisition, it has been developed an Android app where the zone is selected at the entrance of the shop/corridor and starting acquiring fingerprint samples labeled to this zone. Employing this method, it is not required any other task but walking for all the area of the zone, avoiding reference points and other laborious pre-acquisition tasks. During the calibration, the position and the orientation of the smartphones employed could change randomly. The main idea beyond this simplification of the offline calibration phase is to relax the most tedious phase of the set-up of an indoor location system while achieving enough precision for a shop-level ILS. This method is very interesting for an IT company because it allows doing the calibration phase by the own staff of a mall with its own devices, and reduce the operational costs.

Our method is much more cost-effective if compared for instance to [20], where 15-20 Wi-Fi fingerprinting samples are collected in a set of reference points previously-defined in over a grid of 3 meters to generate the reference radio map. Another approach is the well-known crowdsourced method where several users upload the labeled fingerprint [24] when they are visiting the areas of interest. This method requires the voluntary participation of the users to collect the samples for all the building. Our calibration method, **random walking survey**, is closer to work [25], with the difference that the path along the zone does not have to be stated. Only a natural movement around all the indoor surfaces should be addressed without any other requirement. An analogous walking survey method, but following predefined paths, has been tested against reference points method and other methods in [8], showing similar performance while avoiding predefined paths setting. As it will be shown in the Results section, the proposed **random walking survey** presents a cost-effective off-line calibration method for large areas, and it is well-suited for shop-level classification ILS using heterogeneous devices.

C. Location algorithm

Several indoor localization fingerprinting RSSI Wi-Fi algorithms can be found in state of the art. In order to address the hardware heterogeneity and different smartphone models, a well tested and referenced heuristic algorithm called Freeloc [19] has been used. It has been successfully evaluated in several related works with very different topologies and fingerprint acquisition methods [7], [26]–[28].

The core of the Freeloc algorithm is to make the right choice of the parameters δ and RSS_{peak} for generating the correct fingerprint vector related to each AP and for each location. After the calibration phase, several evaluation routes have been implemented using the same random walking survey method along several zones of the mall. The location engine generated by the calibration fingerprint with different δ and RSS_{peak} are tested, and the parameters with the best performance obtained using the mean error meters metric are selected. In this work, Freeloc has been extensively evaluated over the time pass by using test routes with several different devices, following the same random walking method used in the calibration phase.

D. Active location methods barrier

Once the digital map is created, the calibration phase for radio-map acquisition is performed, and the engine location is generated choosing the right parameters, the last requirement for generating the valuable information about the smartphone location of visitors is obtain the fingerprint of the mobile phones as the users are walking through the infrastructure. It has been solved with a small easy-to-integrate library built-in the generic Android app of the mall. The library can be integrated into the app of the mall that the users install for checking cinema timetables, using the discount vouchers, special offers, etcetera. Obviously, with the user permission for the location given by the user, the library acquires the fingerprint as the users move through the mall, providing amenities services to the user with the app installed like VIP services or some fast-pass preferences, is an easy way to obtain installation of the app of the mall. The app is able to acquire fingerprint and send it to the remote engine location where it is analyzed in real time. In this fashion, the recommender service acts using the push notification of Android system, special offers and services can be provided based on the user's location.

IV. TEST SCENARIO

A. Description of the test scenario

The system has been extensively tested in a mall in the South of Spain with a single building. It is an open-air shopping center (the ceiling is only a wooden structure with a cloth cover) with 25.000 square meters distributed on three floors. It has been split into 69 zones (16 on the ground floor, 33 on the first floor, and 20 on the second floor). 57 of 69 zones correspond to a shop, while the remaining 12 zones are related to a portion of a corridor or a portion of the central square in on the ground floor. The corridors have been split into small portions to avoid large zones and to test the performance of the system in this kind of situations. Fig. 2 shows the map and the distribution of the shops and corridors.

Fig. 2. Map of the mall where the ILS has been evaluated

B. Off-line calibration performed

The off-line calibration phase has been executed using the aforementioned random walking survey method with smartphones #1 – #5 (Table III) all at once. We collect several radio maps in each shop/corridor walking with a natural movement. During this phase, the positions of the five smartphones change randomly; sometimes, one of them is in the pocket, and sometimes in the hands.

A single one calibration was performed, which is later used for all the test campaigns. It took 6 hours to calibrate the 69 zones from the mall with a surface of 25.000 square meters. The occupancy level of the mall was not controlled during the offline calibration phase, and it was done in a usual low occupancy day. In later sections, we study how the use of fingerprint acquired by different smartphone affects the performance of the system and the remaining of the performance of the system over time.

C. Validation routes

With the aim of extensively testing the system, four validation routes have been defined. They emulate different client's journeys inside the mall. These routes cover 51 of the 69 zones and 22.000 square meters of the mall. Thus, 89% of the surface is tested with these routes. Each of them passes through different shops, but some corridors are shared by different routes. The number of zones and the total area of each route is defined in Table I, together with the number of different shops per route, and the number of corridor-type zones shared between routes.

TABLE I. ROUTES DESCRIPTION

Route Id	Number of zones	Unique shops / shared corridors	Square meters
#1	14	9 / 5	8,945
#2	19	11 / 8	7,627
#3	21	12 / 9	5,831
#4	19	10 / 9	7,598
Total	51	41 / 10	22,208

For the purpose of measuring and evaluating the overall performance of the system as time passes by, the validation routes are implemented regularly on different days. Moreover, the routes are repeated the same day with different people

occupancy level (low, high) in the mall to evaluate the well-known influence of fading due to the pedestrian walking around fingerprint acquisition zone. Table II shows the periodicity of the routes and the occupancy level of the mall.

TABLE II. PERIODICITY AND OCCUPANCY OF ROUTES

Smartphones	Day	Morning/ Afternoon	Route	Occupancy
#1 - #5	1	Morning	#1 - #4	Low
#1 - #5	4	Morning	#1 - #4	Low
#1 - #5	11	Morning	#1 - #4	Low
#1 - #5	11	Afternoon	#2 - #3	High
#1 - #5	18	Morning	#1 - #4	Low
#1 - #5	18	Afternoon	#2 - #3	High
#1 - #5	38	Morning	#1 - #4	Low
#1 - #10	74	Afternoon	#1 - #4	Low

The path followed in each route inside the shops or in the corridor are randomly selected. The persons carrying smartphones during the validation routes move randomly through the store/corridor area, and the position and orientation of the smartphones are random too (trouser or jacket pocket, in hand in texting position, two smartphones in the same hand), as done in the offline calibration phase.

D. Smartphones used for testing

Several Android smartphones from different vendors and Wi-Fi chipset have been used in the off-line calibration phase and test validation routes. Table III shows the diversity of employed devices.

TABLE III. SMARTPHONES USED IN CALIBRATION AND TESTS

Id	Manufacturer and model	Wi-Fi Chipset	Standard	Dual (2.4/5 GHz)
#1	Xiaomi Mi5	Qualcomm Snapdragon 820	a/b/g/n/ac	Yes
#2	BQ Aquarius M8	Mediatek MT8167B	b/g/n/ac	Yes
#3	Huawei P8 Lite 2017	Huawei/HiSilicon HI1101	b/g/n	No
#4	Huawei P8	Huawei/HiSilicon HI1101	b/g/n	No
#5	LG K11	Mediatek MT6750	b/g/n	No
#6	BQ ElCano	MediaTek MT6577	b/g/n	No
#7	BQ U Lite	Qualcomm Snapdragon 425	b/g/n	No
#8	Xiaomi Redmi Note 1	Mediatek MTK6592	b/g/n	No
#9	Xiaomi Redmi Note 4	Qualcomm Snapdragon 625	a/b/g/n	Yes
#10	Xiaomi Redmi S2	Qualcomm Snapdragon 625	b/g/n	No

It has to be noticed that similar smartphones from the same manufacturer, like #9 and #10, have the same Wi-Fi chipset with the difference that in #10 the dual-band operation is not implemented. Moreover, it could be assumed that smartphones using the same chipset and same frequency bands like #3 and #4 should perform similarly with respect to acquired RSSI levels and scan velocity. However, as shown in Table IV and reported in [5], there exist vast differences between them.

V. RESULTS

A. Analysis of fingerprinting differences

It is worth noting that the WiFi WLAN in the mall is formed by permanent Wi-Fi infrastructure from the owners of the mall, but also private WiFi APs from each shop. Therefore, there may change the number of WiFi APs deployed in the whole mall area from month to month. Therefore, the fingerprint of large areas can undergo many changes due to the variability of constituent APs over time. Moreover, different smartphones detect different APs and receive unequal RSSI levels of the same AP, in a similar situation. An analysis of the behavior of each smartphone used during the calibration phase has been performed to study the differences among them. Table IV demonstrates the differences between smartphones, even with the same chipset, such as the case of #3 and #4. For example, device #3 collects fewer APs per scan than device #4 (21 APs/scan against 32 APs/scan), but it has a higher scan frequency scan rate (699 scans versus 211 scans in the same offline calibration time) and detects 29 APs more.

TABLE IV. DIFFERENCES IN APs DETECTION AND SCAN RATE

Smartphone Id	APs detected (2.4 / 5 GHz)	Mean APs per scan	Scan Number	RSSIs
#1	409/349	49	1033	50637
#2	462/398	67	2293	155290
#3	383/0	21	699	15185
#4	354/0	32	211	6934
#5	240/0	31	749	23816

Further analysis of the evolution of detected APs over time shows high variability. Table V shows the number of different APs detected for smartphone #1 and #2 from calibration, labeled as day 0, and from the validation routes labeled as days 1, 4, 11, 18, 34, and 74, which corresponds with days after the calibration. The actual number of total available APs cannot be analyzed since the validation routes do not cover every zone of the mall.

There are significant differences between the detected APs for each device every day. It is worth mentioning that one day after the calibration, 32 and 51 new APs are scanned for device #1 and #2 respectively. Furthermore, device #1 detects 100 new APs day 34. Therefore, a very different number of APs are detected per each smartphone. In the case of dual-band smartphones, 758 APs and 860 devices are detected for device #1 and #2. It contrasts with the *only* 240 APs detected for device #5. Moreover, the number of APs detected in each validation route shows us a high variability in the presence of APs. Therefore, the system should be able to accurately locate devices which collect an instant fingerprint with a vast difference than the calibration fingerprint. Moreover, the fingerprint generated with each smartphone is highly different between them. With these two key premises (a varying fingerprint in time, and a different fingerprint generated per each device), we will demonstrate in the next section that our proposed system is able to work correctly over a long period of time, and independently of the smartphone used in calibration day.

TABLE V. EVOLUTIONS OF APS OVER TIME

	Calibration day	Day 1	Day 4	Day 11 morning	Day 11 afternoon	Day 18 morning	Day 18 afternoon	Day 38	Day 74
Total of APs #1	758	761	755	757	729	727	679	767	779
Same APs #1	-	729	722	717	683	674	634	667	667
New APs #1	-	32	33	40	46	53	45	100	112
Total of APs #2	860	831	815	809	756	769	730	797	788
Same APs #2	-	780	766	764	714	720	682	747	696
New APs #2	-	51	49	45	42	49	48	50	92

B. Performance over time

A custom location engine is built using the calibration fingerprint from a device. From an instant fingerprint measured from a client's smartphone, the custom location engine infers the ID zone (shop or corridor). The performance metric used is the Euclidean distance between the centroid of the estimated zone and the actual zone. The goal is to minimize the error distance for the whole area.

With the aim of study the performance of the system over time, the validation routes #1-#4 are tested over days 1-74 for each fingerprinting acquired with the five smartphones employed in the offline calibration phase. Cross-validation methodology is used, so the validation data generated with the smartphone used to generate the location engine are discarded. Henceforth, each localization engine is evaluated against the four distinct validation routes generated with the other four devices. Fig. 3 shows the stability in the performance of the systems generated by the fingerprint acquired by each device during time evolution considering the mean error of each sample in the validation route for each location engine and the cross-validation methodology. Device #1 (Dual Xiaomi Mi5) exhibit better performance than the other devices, and it is the most stable over time, having the same mean error at first day and the 74th day. But all the devices show a stable and excellent performance over time, with a 14 meters mean error in the worst case (device #2 day 34).

Fig. 3. Performance of the ILS over time

C. Performance against different smartphones

The five location engines generated have been evaluated with ten different smartphones the day 74 using cross-validation. Fig. 5 shows the CDF error distance for each sample or route #1-#4 using the real labeled zone and the estimated one. The devices #1 and #2 obtain a better performance in the exact success zone (over 60% and 50% each of them), but the device #2 shows a worse error at 90th

percentile. It is worth mentioning that all the systems have around 30 meters of error in the 80th percentile (except the engine generated with device #4 for devices #3 and #5) and 40 meters of error in the 90th percentile (except device #5 for device #6). For better understanding, Fig. 1 has 30 meters distance overprinted. This distance matches with a big size shop or with several small size shops, but it is sufficient error distance for the purpose of the system.

From the analysis of Fig. 5, it can be concluded that the location engine shows an adequate performance independently of the fingerprint acquired per each device. This characteristic allows employing whatever device in the offline calibration phase, not requiring specific calibration hardware, permitting the proposed solution to be scalable and quickly expanding to other malls.

D. Impact of occupancy level

Another engaging property to analyze is the affection of fading due to the surrounding people. The system should work adequately independently of the occupancy level, getting the same performance indistinctly of the number of visitors. For adequately evaluating the performance of the system with different occupancy levels, the routes #2 and #3 have been done the days 11 and 18 twice per day, in the morning with low occupancy and in the afternoon when the number of visitors is sensibly higher. Fig. 4 shows the results of each location engine, for the four routes in the morning (routes day 11 and 18 mornings are grouped) and the four routes in the afternoon (routes day 11 and 18 afternoons are grouped too). For device #1 and #4, the very same performance is achieved in low and high occupancy routes. Devices #2, #3 and #4 show slight differences in 0 meters; however, in 20 meters, the low and high occupancy show the same performance.

Fig. 4. Performance of location engines depending on the occupancy rate

Fig. 5. Performance with several devices

E. Mixing of fingerprint

One way to improve the performance of the system is the mixing of two fingerprinting acquired with two different devices, as proposed in [19]. With the aim of evaluating the performance of generating a location engine with more than one smartphone, the fingerprint of worst performance was mixing and evaluated using cross-validation methodology against the labeled samples acquired with the other smartphones in days 1 and 4. From Fig. 3 and Fig. 4 we can conclude that devices #2, #3 and #4 have the worst performance. Therefore, we mix the fingerprint from devices #2 - #3, and it will be evaluated against label samples from devices #1, #4, and #5 acquired days 1 and 4. The same mix of fingerprint and validation are done for #2 - #4 and #3 - #4 devices fingerprint engines.

Fig. 6 (a) shows the performance in mean error distance of location engine generated by device #3, device #4 and the mix of #3 and #4 using cross-validation (only labeled samples of devices #1, #2 and #5 are used), showing a better performance when the mixing of #3 and #4 are used. Fig. 6 (b) shows the performance, again using mean error distance metric when the location engine is generated using device #2, device #3 and the mix of #2 and #3 using cross-validation, showing a better performance when the mixing of #2 and #3 are used. In the last situation, Fig. 6 (c) shows the performance of cross-validation of the engine generated with device #2, device #4, and the mix of #2 and #4. Once again the best performance is achieved by the mix of two fingerprints.

Fig. 6. Mean error of fingerprint generate by device #3, device #4 and the mixing of devices #3 and #4

CONCLUSIONS

In this work, a complete shop level, affordable, and scalable ILS has been proposed and extensively evaluated in a medium size mall with several devices over time. The most laborious and the most challenging phases of the ILS creation, i.e., the digital map creation and the off-line calibration phase, have been implemented using the proposed random walking survey fingerprint acquisition method together with the Jinedit open source tool for digital maps (based on the indoor GML standard). With the combination of these technologies, the system can be deployed in whatever mall with a densely deployed Wi-Fi APs infrastructure.

The evaluation of the ILS presents adequate performance over time independently of the device employed in calibration and also using several devices for testing. Moreover, the performance of the system does not vary over

a considerable period of time (70 days). Another issue tested is that the system does not have variability independently of the number of visitors in the mall.

Similarly, one way to enhance the performance of the system without further complexity is to carry out more than one devices in the off-line calibration phase. In this sense, the evaluation of mixing several radio maps acquired by two devices has shown better performance than using a single radio map.

Finally, the system has been implemented in another mall for further evaluation, obtaining similar results which will also be addressed in the oral presentation. In the future, the system can be enhanced by implementing preprocessing of fingerprint samples, with the evaluation of other location algorithms, and also including postprocessing of the acquired fingerprint to include realistic movement models.

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Artículo 6

An automatized contextual marketing system based on a Wi-Fi indoor positioning system

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Article

An Automatized Contextual Marketing System Based on a Wi-Fi Indoor Positioning System

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Abstract: A complete contextual marketing platform including an indoor positioning system (IPS) for smartphones is proposed and evaluated to later be deployed in large infrastructures, such as malls. To this end, we design and implement a novel methodology based on location-as-a-service (LAAS), comprising all the required phases of IPS generation: mall digital map creation, the tools/procedures for offline calibration fingerprint acquisition, the location algorithm, the smartphone app acquiring the fingerprint data, and a validation procedure. To select an appropriate fingerprint location algorithm, a comparison among K-nearest neighbors (KNN), support vector machine (SVM), and Freeloc is accomplished by employing a set of different smartphones in two malls and assessing different occupancy levels. We demonstrate that our solution can be quickly deployed at shop level accuracy in any new location, resulting in a robust and scalable proposal.

Keywords: indoor location system; smartphone location; area-level positioning; Wi-Fi fingerprint; contextual marketing

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1. Introduction

Nowadays, most large retail companies focus their marketing strategies on knowledge of customer behavior in all the commercial channels. These marketing techniques are known as omni-channel strategies [1]. The overlapping of customers' online and offline behavior requires awareness [2] to create successful, specific marketing campaigns targeting particular segments of the population. The key is to study both types of behavior before launching any marketing strategy. Online customer behavior is studied in detail through the use of web/app analytics and cookies. Currently, research efforts are mainly addressed at learning about offline behavior; when the customers arrive at points-of-sale. Therefore, aspects such as the time that customers stay inside a given shop, the frequency of these visits, or the routes followed by customers are some of the inputs employed to increase knowledge about potential buyers [3]. Suitable analysis of this information provides marketing departments with the opportunity to optimize efforts which could influence purchasing decisions and define more effective contextual marketing campaigns. However, difficulties arise when these campaigns are carried out in indoor environments in real time. In this case, an indoor positioning system (IPS) is required to learn about consumers' offline behavior. In order to increase the success of a contextual marketing platform, the system employed to plan and manage an omni-channel marketing campaign should include an IPS module.

Malls are essential locations for retailers. Mall owners often have marketing teams in charge of increasing the frequency of visits, and once they have managed to increase traffic within the mall, they try to influence purchasing decisions to maximize spending.

Marketing teams, with a marketing manager at the forefront, are responsible for defining, planning, and managing both online and offline marketing campaigns using contextual marketing platforms. Consequently, malls are obvious environments in which to apply IPSs. As we describe in this work, an IPS is one of the most distinguishing elements of a contextual marketing platform, although we must not forget other technological tools that are necessary to implement a complete and useful solution. The components that must integrate a complete platform to learn about online/offline behaviors are the following: (i) a customer relationship management (CRM); (ii) a content manager system (CMS); (iii) a key performance indicator (KPI) panel; (iv) a mailing and push notification service; (vi) the IPS itself; and (vii) a mobile app. As the first contribution of this work, we delve into the implementation of all the aforementioned elements of a contextual marketing platform, their interconnections, and how their use can increase knowledge about potential customers. The IPS is the module which obtains the location of users inside the mall. Once the position of each visitor is determined, it is an input parameter of the contextual marketing platform. Expressed in a different way, the output of the IPS is employed as input in the contextual marketing platform, providing so-called location-as-a-service functionalities. To this end, customer location and tracking through the use of smartphones inside infrastructures are studied in this work.

As can be observed, the IPS is the engine of the contextual marketing platform. Thus, one of more important aspects is how to accomplish its implementation. In this sense, there is no standard solution that determines position in indoor environments, and this situation provides new engineering challenges. Different alternatives have utilized technologies like Wi-Fi [4], Bluetooth [5], ultrawide band (UWB) [6], or radio frequency identification (RFID) [7]. As Wi-Fi technology is widespread in malls, we discard others, such as Bluetooth, UWB, and RFID technologies. These technologies require the deployment of new infrastructure in the mall with high operational and maintenance costs, increased by the use of beacons and other ad hoc hardware. Moreover, these technologies are out of the coverage range to locate people through a mobile phone.

With respect to the inputs of the location algorithm to implement the IPS module, diverse Wi-Fi smartphone IPS solutions can be found in the scientific literature, such as [8,9], where the so-called inertial measurement unit (IMU) sensors, such as barometers, accelerometers, gyroscopes, or magnetometers, are employed. Merging the data from these sensors with Wi-Fi fingerprint information, precise pedestrian dead reckoning (PDR) can be generated. This system is capable of detection of the direction of movement [8], stop/walk detection, and step counting [9], among other things. The IPS obtained by these sensors along with Wi-Fi fingerprint data can be extremely precise. However, these solutions have a definite disadvantage: they consume a lot of battery power. A system conceived to operate in a large infrastructure during extended time periods must guarantee robust smartphone functionality. Under these premises and prioritizing sustainable battery consumption, one of the design principles of our system is to employ only Wi-Fi received signal strength indicator (RSSI) fingerprint information. Taking this requirement into account, better performance related to battery use and sustainability in comparison with those that employ IMU sensors is ensured, however, location is compromised. In our case of use, a mall, the automatized actions of the contextual marketing platform do not require centimetric accuracy; marketing activities are effective at shop-level granularity. Consequently, we established shop-level precision as a design requirement for our IPS solution.

The drawbacks associated with our proposal are related to the limitations of employing only a Wi-Fi signal: (i) the IPS will be affected by access point (AP) density variations because it depends on the network infrastructure, (ii) smartphone heterogeneity (different manufacturers, models, etc.) implies different RSSI values, even when using the same chipset [10], (iii) the variability of mall occupancy, which impacts aspects such as signal propagation [11], and (iv) the Wi-Fi fingerprint, which frequently changes due to the variation in the number of active APs as time goes by [12]. To the best of our knowledge, there are no studies in the scientific literature comparing Wi-Fi fingerprint algorithms

considering these premises in a large, real infrastructure. With the aim of filling this gap, we evaluate three well-known algorithms to be employed as Wi-Fi inputs for our IPS module. These algorithms are the following: K-nearest neighbors (KNN) [13], support vector machines (SVMs) [14], and Freeloc [15]. In a recent study [16], different RSSI fingerprinting indoor location algorithms were compared. The results show that KNN offers appropriate performance through a dataset composed of 4648 fingerprints acquired by using a static procedure during one day in a university building. SVM has been evaluated, showing reasonable accuracy in several indoor scenarios at the shop level [17]. Freeloc can face the problem of dealing with heterogeneous devices and has been extensively evaluated in [18]. Having these inconveniences in mind, as a second contribution, we have conducted an analysis and comparison of IPSs implemented with these three algorithms. Moreover, we have considered the aforementioned problems in malls, such as hardware heterogeneity, variations in AP density over time, and how different occupancy levels affect signal propagation.

The accuracy of the algorithm employed in indoor locations is crucial but the rest of the processes and tools required for the creation of the entire IPS are no less important. In general, the stages deployed to achieve an accurate indoor location solution are defined in [19] and are the following: (i) digital map generation, (ii) the offline calibration phase, (iii) the system build-up/positioning algorithm for localization tasks, and iv) launching and testing. In this work, all the resources and methodology employed in each phase of our IPS, together with every one of the specific processes and tools used to obtain a practical and scalable solution from the perspective of a small-medium enterprise (SME) IT company, are described in detail. Therefore, as our third contribution we have designed, implemented, and thoroughly evaluated a complete IPS module, taking into account the following premises: (i) it employs the already deployed Wi-Fi access points in malls for connectivity purposes, (ii) it considers current market smartphone heterogeneity, (iii) our solution is deployed by non-trained personnel, (iv) it is scalable in all the aspects of the deployment as will be further detailed, and (v) it provides information referring to user location to the contextual marketing platform, resulting in location-as-a-service functionalities.

Concerning the already published works about the implementation of IPSs in large infrastructures, there are studies which provide positioning services in scenarios similar to ours. The COEX mall [19] was the first to be supplied with an indoor location and navigation service based on the analysis of RSSIs. However, several dozens of calibrators along with some weeks of work were required for its implementation. Similar to this work, Li et al. [20] tested their technology in large malls, considering the heterogeneous mobile device problem in these scenarios, offering an accuracy below 2 m. However, ad hoc APs have to be installed in the mall. Mathisen et al. [21] showed a comparative evaluation of several indoor positioning techniques in a large university hospital. In this work, the authors evaluated several IPS solutions from data gathered on different days and at different times, both in static locations and moving throughout the building. The results illustrated the challenges involved in transferring data from a small, controlled environment, such as a small office environment, to a large, dynamic building complex. Furthermore, this work employed samples acquired only on two days and, therefore, did not evaluate the evolution of the different IPSs over the time. Another interesting approach is in [22]. The authors proposed a zone-level IPS by applying neural network techniques, and they compared it against the KNN algorithm, achieving a slight change in accuracy. However, it was deployed in a university building with only 24 APs, and the evolution of the IPS over time was never tested. There are also commercial products for the generation of IPSs employing Wi-Fi signals, like Ekahau RTLS (now renamed to AiristaFlow) [23]. However, these IPSs require an exhaustive calibration and the use of specific and complex calibration tools. Dealing with the drawbacks of the aforementioned IPS solutions is our fourth contribution.

Finally, as a fifth contribution of this paper, we publish a complete dataset fingerprint which provides details of our proposed solution. The database is open to the scientific

community including all the information collected during the calibration phase together with the fingerprints acquired in the validation stage. Note that other datasets available for indoor positioning have also been published in the past. In [24], datasets and supporting material employed during the Indoor Positioning and Indoor Navigation (IPIN2017) competition can be found. Another interesting work is by Lohan et al. [16], which provided a full measurement package composed of crowdsourced Wi-Fi fingerprints as well as an intensive review of other indoor Wi-Fi datasets, pointing out their availability, features, and limitations. Mendoza-Silva et al. [25] created a dataset containing measurements collected in a large building for an extended period of time. In this work, the results were obtained by employing a single device. Although this is an important drawback, the time dedicated to this experiment was long enough to detect variations in the Wi-Fi environment and to validate other algorithms. The dataset provided by [26] is also worth mentioning. It includes the following two aspects: (i) RSSI values obtained in an office environment of around 200 m², and (ii) a fingerprint database of magnetic measurements. The main disadvantages of this dataset are the reduced size of the modeled space and the fact that only a single device was used to perform the tests. Some of the authors of this paper also published another dataset [27] which contains RSSI data collected in a large, multi-floor building, by employing several devices carried by different users. This implies collecting geotagged samples which are useful to validate other IPS solutions.

The dataset included in the current paper is available at Zenodo [28], a general-purpose open access repository developed under the European OpenAIRE program. This repository allows researchers to store and publish datasets, software, reports, and any other research-related digital artifacts with the main aim of presenting this information to the rest of the community. Our dataset allows other researchers to carry out their own validation tests since it includes the RSSI measurements collected during the offline phase to build fingerprint models at the shop level. Additional information about our dataset and best practices is provided in the rest of the paper.

To summarize, aside from the extensive comparison and discussion of three of the most well-known algorithms employed in IPS generation (SVM, Freeloc, and KNN), we detail all the considerations necessary to provide a complete and effective contextual marketing platform. The interactions between modules, their architecture, and functionalities are also detailed. This work is structured as follows. Section 2 details the methodology followed for: (i) the architecture of the contextual marketing platform including all the information related to the generation of the IPS, (ii) the malls, smartphones, and validation routes employed in the comparison of the different algorithms, and (iii) the Wi-Fi fingerprints generated and shared in an open access repository. Section 3 illustrates the results of the comparison among the aforementioned algorithms, which are later discussed in Section 4. Finally, Section 5 concludes the paper.

2. Methods

This section describes the main modules comprising the contextual marketing platform developed here, focusing on the procedure and tools required for the generation of the IPS. Once the ISP is fully explained, three algorithms (KNN, SVM, and Freeloc) employed to create the engines of IPS solutions, that are key to analyzing its best performance, are detailed. Later, we indicate the malls where the validation procedure was evaluated, the routes selected, and the smartphones employed. Finally, we describe the Wi-Fi fingerprint dataset generated in this work.

2.1. Contextual Marketing Platform Architecture

“Marketing automation” is a new paradigm in the relationship between retailers and customers. As was defined in [29], it can be summarized using the following example: “As retailer X, what do we tell customer Y when he/she arrives on Monday morning?”. Marketing automation, together with the omni-channel strategies already mentioned in the Introduction, are faced with the challenge of merging clients’ online and offline behavior.

The questions to answer under this paradigm, expressed again through examples, are: “What do we say to a customer who signed up to our mobile app or website two months ago but has never come to our facilities?” and “How do we send the message? Should we send a push notification or should we send an email?”. The answers to these questions are carefully studied by the retailers’ marketing teams and the owner of the mall and implemented as marketing actions. Thus, the automation of these campaigns must be planned since, if not, personnel would have to carry out these actions, and this could make the marketing proposals nonviable. One way to perform effective and automatized marketing campaigns is to use a contextual marketing platform. However, the whole paradigm of contextual marketing, marketing automation, and omni-channel can only be covered if the platform that manages the marketing activities includes an IPS to provide location-as-a-service (LAAS).

In this work, a contextual marketing platform is designed and developed for owners and retailers. It is placed in a mall, and an IPS is implemented to locate and track customers’ smartphones. Explicit permission must be given by users to allow the IPS to know their position inside the mall, the time they spend there, the frequency of their visits, the hour they arrive at the center, etc. These location data are used as input in the automated marketing campaign.

The marketing system stores the information provided by the user in the registration phase both in the app and on the website. Moreover, user interactions with the app and with the website together with their movements in the mall are stored. Meanwhile, mall marketing managers register the campaigns, promotions, and events that could be offered to visitors in the content manager system (CMS). Each of these elements causes different activation mechanisms to interact with users in particular ways. For instance, a specific marketing campaign with some type of discount could be sent by email to users who frequently visited the mall but who have not come in the past two weeks. Another example is that a push notification with a promotion can be sent to customers located in determined areas of the mall to move them to less-visited areas. Analyzing these examples, we can say that without a powerful indoor location system, it would be complicated to implement marketing actions in accordance with the behavior of offline visitors. Thus, these novel functionalities provide added-value tools to marketing managers. The complete detailed architecture of the designed system, including the customer relationship management (CRM), content manager system (CMS), mobile app, indoor positioning system (IPS), push platform, mailing platform, and key performance indicator (KPI) panel, is depicted in Figure 1.

2.1.1. Customer Relationship Management (CRM)

This module of the system (labeled as CRM in Figure 1) is in charge of managing all the information related to the users who have previously registered using the mall website or app. A complete and detailed record of each user is stored with all the information related to her/him. The data employed for the signing-up process, such as email, birth date, marital status, etc., are added to the information generated by the use of the app, the use of the website, and the location information generated by the IPS (if the user gives explicit permission).

The CRM also generates segments of users [30] according to different criteria. In the marketing field, a segment is an aggregation of users with common features or similar affinities. A marketing manager can specify the conditions required to place a user in a specific segment by using the filters available in the module. When new content is created in the CMS, a notification can be sent to one or several segments. If the segment of the user is not relevant to this kind of content, it is published in the mobile app and on the website but the user is not notified. With the use of segments, specific information can be sent only to users who fulfill certain conditions.

Figure 1. The complete architecture of the contextual marketing platform.

With the combination of segments from the CRM and the IPS (explained later), we are able to automatize messages, such as welcome messages or one-day special offers, when users arrive at the mall. Furthermore, surveys can be sent when users leave the shopping centers, asking them to evaluate their shopping experiences to provide quality control.

2.1.2. Content Management System (CMS)

The CMS is the module where the information regarding the mall is introduced to be published (see Figure 1, CMS module). Drupal, WordPress, or Alfresco [31] are some of the well-known CMSs for managing the content of web platforms. In our case, a complete and novel CMS has been developed since we need specific functionalities related to marketing calls-to-action.

The information in the CMS can be related to new proposals, new services available in the mall, or relevant information that managers wish to communicate to their visitors. When the information is completed, with the help of an easy-to-use editor, it can be published on the website, the mobile app, or both. Moreover, an email or push notification can be sent to users in a specific, previously defined segment. The CMS also allows notification triggers to be configured. Some examples of the use of these functionalities are sending emails with information if users have not accessed the website for a month, or sending push notifications with discounts for, for instance, breweries to the users who have checked cinema timetables in the mobile app and have not visited the mall.

2.1.3. Mailing and Push Notification Platform

Nowadays, one of the most effective communication channels in marketing is email. Email campaigns, or email actions, have great impact as they are direct ways of communicating with customers. One of the advantages of our CRM is that it facilitates marketing campaigns using email communications where marketing managers make use of previously defined customer segments. In our proposed solution, information about users' visits to shopping centers can be employed to establish this segmentation. Considering location data as well as other customer purchasing information, certain patterns of behavior can be estimated, which helps make these email campaigns much more effective. The mailing and push platforms are depicted in Figure 1 below the CMS module.

In the retail context, it is crucial to define the exact moment at which communication with the customer should be carried out; the goal is to contact clients when they are most receptive to the information they are going to receive. Additionally, mailing reception should not provoke customer rejection, resulting in them unsubscribing from the newsletter or uninstalling the app.

The fact that customers install one of our apps in their smartphones implies location services running in the background. This allows us to communicate with them by sending geo-located push notifications. These notifications can be configured in two ways. Firstly, they can be scheduled to be sent at a certain time to a specific customer segment, as discussed above in the case of emails. Secondly, what gives more relevance to this module is knowing where customers are moving and that they receive a geo-located push notification with information about what is happening where they are moving in real time.

2.1.4. KPI Panel

One of the most important aspects when evaluating the business model of a mall is to be able to measure the impact of marketing actions. For instance, the possibility of studying the evolution of customers during a Halloween campaign with respect to the data obtained for the same time period of the previous year could be very valuable. The increase or decrease in the number of visits or greater or lesser interaction with the app are issues that can be measured, providing added-value information to determine whether the actions carried out achieve the expected results or not. In other words, our platform, supported mainly by our IPS, becomes a decision-making tool at the management level. Putting this functionality into context with the previous sections, our platform is a complete business-level tool which handles aspects such as operations, communications, special offers, or services, among other things. Figure 2 illustrates the visualization of some KPIs (see Figure 1, KPI module) related to occupancy levels.

2.1.5. Indoor Positioning System (IPS)

As previously mentioned, the IPS (see Figure 1, IPS module) is one of the main elements of the contextual marketing platform. Without the location of the user, the LAAS proposals could not be implemented. This is one of the reasons why our IPS-based solution has been designed with the aim of minimizing the effort needed from personnel in all the deployment phases. This is a real and scalable system that can become the basis of business strategies. Our solution is scalable because it is deployed and maintained with minimum effort in any infrastructure, independently of the country or region where it is located. With these conditions of minimum effort in deployment and maintenance, the system can be used worldwide without an exponential increase in the resources required.

Figure 2. Examples of the KPI panel for marketing purposes in a mall.

Consequently, to achieve a scalable system that can be easily deployed in hundreds of buildings, all the deployment phases must be efficient. The design and implementation of an IPS solution must comprise the phases described in [19] and illustrated in Figure 3, namely: (i) digital map generation, (ii) the offline calibration phase, (iii) a system build-up/location algorithm for localization tasks, and (iv) launching and testing. A fully scalable system can be achieved if the aforementioned phases are performed with reasonable time and effort. For instance, if several workers are required to perform the offline calibration phase over several days, the system is not scalable because it cannot be easily deployed worldwide. Another example is if the computing requirements of the location algorithm and/or the cost of processing the location queries demand high processing capabilities, then the solution is not scalable because locating thousands of visitors is not an affordable task.

In the following subsections, we describe all the considerations referring to the design and implementation of an IPS-based solution in each of its phases. The goal is to demonstrate the feasibility of installing our solution anywhere around the world and providing LAAS to the contextual marketing system.

Figure 3. Phases of IPS generation.

Offline Calibration Phase

According to [19], the acquisition of the radio map (fingerprint of each area to later be used in the location algorithm) during the offline calibration phase is one of the tasks that consumes the most time during the setup procedure of an IPS. In [14], a 3×3 m grid was defined with reference points, and fifteen people were employed to calibrate the 10,000 points over two weeks. In our case, this approach cannot be employed because it is not scalable. In accordance with our requirements, the calibration phase has to be performed in a shorter period of time. At the same time, a stable and representative fingerprinting of each area that will be monitored must be acquired over time. Moreover, keeping the aim of scalability in mind, if specific hardware or several well-trained calibrators have to be employed for several weeks, the options for adopting the appropriate solution decrease. To address these drawbacks, we select the *walking random survey method* together with an ad hoc easy-to-use Android app. With this procedure, the person in charge of calibration uses an Android smartphone with our app installed. The calibrator will simply select the area to calibrate in the app, and then he/she will walk around the selected shop/corridor covering most of its surface. The app will collect the RSSI level of the detected APs and will store it together with the label of the area selected. The position and the orientation of the smartphone can randomly change while the calibrator is walking across the shop/corridor. The *walking random survey method* avoids using other time-consuming precalibration tasks, such as reference points.

Once all the areas have been calibrated, the labeled fingerprints are dispatched to the database; they will be the input data in the location algorithm, thus generating the location engine. The offline calibration phase of a mall can be performed in a few hours with the help of a mall staff member employing the calibration Android app and the digital map generator (explained in the next section) together with the calibration procedure.

However, this method of generating a radio map has some disadvantages. First of all, human error is introduced when the calibrator has to select the correct area in the app to label the fingerprint. This can become a source of error because a different location might be selected and the samples would be labeled in the wrong area. This error is easily avoided in malls because the majority of the areas are shops with lighted signs where the name of the display corresponds to the name in the calibration app. Moreover, the app is very user-friendly and intuitive, and the people in charge of calibration can be instructed to avoid this error. Even if an area has been mislabeled, the validation phase, detailed in the following section, has a mechanism to detect this kind of error, and this area can be recalibrated. There is another disadvantage of the *walking random survey* procedure. Although this is a method that allows the fingerprints of a mall to be obtained in a few hours, it has the drawback that changes in the orientation and position of the calibrator can produce drastic

changes in RSSI levels. Walking in one direction or another could result in changes of several dB. These changes produce greater errors in comparison with other calibration procedures where IMUs or other smartphone sensors are employed. Nevertheless, the results obtained (and explained in Section 4) illustrate that shop-level accuracy can be achieved with our proposed solution. Therefore, we have chosen a trade-off between an affordable calibration procedure and sufficient accuracy for the system's purpose.

Digital Map Creation

Prior to the calibration phase, a digital map must be created of the relevant mall infrastructure. These areas, along with the calculation of their Euclidean distances, are stored in a database. Then, the calibration app reads the name of the areas to be calibrated from this database. These areas are input parameters to be selected by the person performing the calibration. To generate the digital map, we extended the code of the open-source tool called JIneditor [32], designed by Spatio-Temporal Databases Laboratory at the Pusan National University in South Korea and based on the indoor GML standard [33]. Our system does not require high precision; the shop/corridor level is enough. That is, our solution is far from being a dead reckoning system or an indoor navigation system.

Note that only a list of the shops and the floorplans of the mall are required to generate the digital map. Then, the aforementioned calibration app is installed on any Android smartphone and is fed the names of the shops. A mall staff member will walk with the app turned on, pointing out the shop where she/he is in each instant. Therefore, the samples of the RSSIs of the Wi-Fi APs that are already deployed are stored and labeled with the names of the shops. When all the areas have been covered, the samples are sent to the fingerprint database (see Figure 1) to be employed in the following phases of the IPS creation process.

Location Algorithm

The IPS is the module which determines the location of the users inside the infrastructure. Employing the samples acquired from the offline calibration samples, a location engine has to be generated. When a customer with the app installed visits the mall and the RSSIs are sampled, the values are sent to the IPS module, which localizes the position of the user's smartphone. As previously discussed, due to battery constraints, only the RSSIs of the already deployed Wi-Fi infrastructure is employed. Note that our solution avoids the installation of new hardware infrastructure and the use of IMUs or other additional smartphone sensors.

Several indoor location algorithms for this purpose can be found in the scientific literature [34]. To select which one performs the best, considering our requirements, we have compared three of the best-known indoor location algorithms: k-nearest neighbors (KNN), support vector machines (SVMs), and Freeloc. In a recent comparison of RSSI fingerprinting indoor location algorithms [16], KNN obtains the best result for a dataset acquired in a complete building, as is our case. SVM has been evaluated in several indoor scenarios with proper accuracy at the shop level [17]. Freeloc [15] has also been evaluated and it can have problems with device heterogeneity. However, to the best of our knowledge, there is no study about the performance of the aforementioned algorithms in the case of large infrastructures with shop-level accuracy, hardware heterogeneity, variations in the number of APs over time, and the effects of differing occupancy levels. Details of the different algorithms are presented in the following paragraphs:

- **KNN.** A simple and popular location method which calculates the distances between RSSI fingerprints. When fingerprint scans, including the RSSIs of the APs detected, are acquired, they are sent to a remote server. This server sorts the fingerprints collected in the same order as the ones stored to calculate the distance between them later. Using

the Euclidean distance metric, the comparison between the stored fingerprints and the scanned fingerprints follows this equation:

$$\arg \min_{f_{Li} \in F} \sqrt{\sum_{i=1}^k \|f_i - f_{Li}\|}$$

where f_{Li} is each of the fingerprints acquired during the offline calibration phase in locations $\{L_0, L_1, L_2, \dots, L_n\}$. Therefore, KNN chooses the area that has the minimum distance between k most similar stored fingerprints.

- **SVM.** A machine learning algorithm which allows discrimination and regression problems to be solved, with the possibility of adapting them to a multi-class situation. The classification is performed by finding the hyperplane that differentiates all the data of one class from the others. In our case, the classes are shops and the data employed for the classification are the RSSIs from the APs acquired in each of the areas.
- **Freeloc.** A heuristic algorithm that generates a unique vector with the sorted APs according to the RSSI values for each location. When a fingerprint has to be classified, it is sorted and compared with each of the stored vectors. The pseudocode of Freeloc is depicted in Algorithm 1:

Algorithm 1 Estimate the location

Input: fingerprint data $fp_{unknown}$
Output: estimated

```

1:   $score \leftarrow 0, score_{MAX} \leftarrow 0$ 
2:   $value_{MAP} \leftarrow \{\}$ 
3:
4:  for each possible  $fp_{lx}$  in the radio map do :
5:    for each  $KEY_{unknown}$  is  $fp_{unknown}$  do :
6:      if  $KEY_{unknown}$  is found in  $fp_{lx}$  then :
7:         $value_{MAP} \leftarrow VALUE$  vector where its  $KEY = KEY_{unknown}$ 
8:        for each  $BSSID$  in  $KEY_{unknown}$  do :
9:          if  $BSSID$  is found in  $value_{MAP}$  then
10:            $score \leftarrow score + 1$ 
11:         end if
12:       end for
13:     end if
14:   end for
15:   if  $score > score_{MAX}$  then
16:      $score_{MAX} \leftarrow score$ 
17:      $l \leftarrow l_x$ 
18:   end if
19: end for
20: return  $l$ 

```

In the Results section, the performance of the different algorithms over time is evaluated by the dataset acquired in two malls using smartphones from different manufacturers.

2.1.6. Location-Based SDK to Overcome IPS Barriers

As described in the Introduction, one of the hardest to solve barriers of IPS solutions and, therefore, our contextual marketing system, is to motivate potential visitors/customers to participate in these localization tasks. To this end, one of the main elements of our scheme is a mobile app. It has to be installed on each visitor's smartphone to collect fingerprint data while they walk through the different shops. Note that the location task is performed on the server side of the IPS, and the fingerprint data acquired by visitors have to be sent to a remote storage location where the indoor position is computed.

To overcome this barrier, we have developed an easy-to-integrate SDK which can be built into the corporate app of the mall. The mall provides information in its app about movies and other events, special discounts, vouchers, promotions, specific campaigns, etc. Using this tool, along with the mechanism provided by the CRM and CMS, the mall has a direct channel of communication to promote and disseminate specific contents for specific segments of users. When the users install the app, they are invited to receive special promotions once their locations are known. In particular, those users who participate in location data generation through the app can receive advantages in terms of faster Wi-Fi, free Wi-Fi hours, or free playroom services. Once the app has been installed and permission by users has been verified, fingerprint data are obtained every few seconds. This information is compressed, and sent to the server where the IPS is installed. In return, the app notifies the visitors in real time about ad hoc special offers based on their location by means of push notifications.

2.2. Validation Scenarios

Our IPS-based solution has been evaluated in two different single-building malls, both located in the southeast of Spain. Shopping mall 1 is composed of three floors (more than 25,000 square meters) and has a wooden roof structure with big holes covered by a tarp. Mall 2 is divided into two floors and is more than 40,000 square meters. Figure 4 illustrates the different architectural features of mall 1 and mall 2.

Figure 4. Panoramic image of each of the shopping malls where the IPS has been evaluated: (a) mall 1 has three floors and a wooden, cloth-covered roof structure, (b) mall 2 has two floors.

Mall 1 has 69 different areas distributed across three floors. Fifty-six of these areas are shops (14 located on the ground floor, 27 on the first floor, and 15 on the second floor). Note that, in our IPS, each shop is a different area. The remaining areas are corridors and a square, with the following distribution: the main square, located on the ground floor, which has been split into two areas; three corridors on the first floor which have been divided into six areas; and, finally, four corridors on the second floor that have been divided into five areas. Therefore, there are 13 areas not categorized as shops. The main reason for splitting the corridors/squares into areas is to avoid large areas since a corridor can traverse the entire shopping center. This is also required to correctly compute the Euclidean distance between areas.

Mall 2 has 113 areas distributed as follows: 92 shops on two floors corresponding to one area for each shop (59 shops are located on the ground floor and 33 on the first floor); two squares and four corridors located on the ground floor have been split into 12 areas, while two squares and three corridors on the first floor have been divided into nine areas in our IPS. Figure 5 illustrates each floor of mall 1 and mall 2.

Figure 5. (a) Mall 1: ground floor (left), first floor (center), and second floor (right). (b) Mall 2: ground floor (left) and first floor (right).

2.3. Smartphones Employed in the Calibration and Validation Processes

The offline calibration phase and the validation process were performed using different Android smartphones. As is well known, even smartphones sharing the same Wi-Fi chipset measure different RSSI values [10]. The reason for this is that smartphones differ in their antenna orientation and size, in the materials used to make them, or in their software implementation, among other things. It is remarkable that smartphones #9 and #10 are made with the same Wi-Fi chipset; however, #9 is dual-band and supports Wi-Fi standards 802.11 a/b/g/n, while #10 is single-band and only supports standards 802.11 b/g/n. Table 1 details the Android smartphones employed in our study and whose data compose the dataset proposed here.

Table 1. Features of the smartphones employed in our study.

Id	Model	Chipset	802.11 Standard	Dual-Band (2.4/5 GHz)	Ref
#1	Xiaomi Mi5	Qualcomm Snapdragon 820	a/b/g/n/ac	Yes	[35]
#2	BQ Aquarius M8	Mediatek MT8167B	b/g/n/ac	Yes	[36]
#3	Huawei P8 Lite 2017	Huawei/HiSilicon HI1101	b/g/n	No	[37]
#4	Huawei P8	Huawei/HiSilicon HI1101	b/g/n	No	[38]
#5	LG K11	Mediatek MT6750	b/g/n	No	[39]
#6	BQ ElCano	Mediatek MT6750	b/g/n	No	[40]
#7	BQ U Lite	Qualcomm Snapdragon 425	b/g/n	No	[41]
#8	Xiaomi Redmi Note 1	Mediatek MTK6592	b/g/n	No	[42]
#9	Xiaomi Redmi Note 4	Qualcomm Snapdragon 625	a/b/g/n	Yes	[43]
#10	Xiaomi Redmi S2	Qualcomm Snapdragon 625	b/g/n	No	[44]

2.3.1. Offline Calibration Process

Both malls were calibrated by means of the smartphones labeled #1–#5. The main features of these smartphones are shown in Table 1. The time employed to calibrate mall 1 was six hours, while for mall 2, ten hours were required. The calibration process followed the *random walking survey method* described in Section 2.1.5 During the calibration process, five smartphones were carried all at once, without any fixed position/orientation, while the areas were checked. That is, during fingerprint collection, the smartphones were in pockets, handheld, or even in the backpack of the person who was performing the calibration process.

As a rule, the most time-consuming task for deploying an IPS is the offline calibration phase [19]. However, with the proposed *random walking survey method*, this operation can be performed in reasonable time. Moreover, since neither specific smartphones nor well-trained calibrating operators are required, our solution presents greater scalability. The calibration process using the Android app is learned with a few minutes' training. Additionally, the measurements are taken by employing any Android smartphone. This entails an associated problem: the fingerprints acquired can be very different depending on smartphone characteristics since there are smartphones that implement dual-band technology, have different sampling velocities, are more or less sensitive, etc. Therefore, our location algorithm must be able to derive appropriate location results regardless of the smartphone employed in the calibration phase. In Section 2.4, the differences among the fingerprints acquired with each smartphone are illustrated.

Another remarkable aspect of our calibration process is that normal mall operations were not affected. All the calibrated surface was covered while both malls were open, without considering their occupancy levels and without interfering with their normal routines.

In further sections, we will demonstrate how the performance of our solution is not influenced by occupancy levels (note that the measurement campaign was carried out during opening hours, with varying numbers of clients) and how IPS accuracy does not depend on the smartphone used in the calibration phase.

2.3.2. Validation Routes

Once the calibration phase was finished, four different validation routes were traced in each mall. The objective was to test the accuracy of our IPS-based solution over time but on different days. The routes simulate the movement of visitors/customers during a trip to the mall. Regarding the validation routes in mall 1, 51 of the 69 areas were covered, which was equal to 22,208 square meters out of a total of 25,000. Therefore, 73% of the shops/corridors together with 89% of the total surface of the mall were included in the validation process. Regarding mall 2, 58 of the 113 areas were mapped, covering a surface of 33,4402 square meters (51% of the shops and 83.5% of the total surface of mall 2). The details of each route are illustrated in Table 2. Note that in both malls, the validation routes go through different shops; however, the corridors are shared by different validation routes. Therefore, the total (i) areas and (ii) square meters only compute the different areas.

Table 2. Routes implemented for validation purposes, showing both the number of areas and the number of shared corridors where RSSI samples were acquired. The square meters covered for each validation route are also indicated.

Route Id	Mall	Number of Areas	Single Shops/Shared Corridors	Square Meters
#1	1	14	9/5	8945
#2	1	19	11/8	7627
#3	1	21	12/9	5831
#4	1	19	10/9	7598
Total Mall 1		51	41/10	22,208
#1	2	17	10/7	5579
#2	2	17	10/7	11,657
#3	2	19	9/10	9279
#4	2	18	9/9	10,027
Total Mall 2		58	38/20	30,642

One of the main purposes of this work is to evaluate the operation of our IPS solution. To this end, we planned four validation routes and several measurement campaigns on different days with different environmental conditions. Moreover, we took into account the variation in the number of visitors in each mall. Table 3 shows the smartphones employed in each of the validation routes, the days elapsed after the offline calibration phase, what route is tested, and the occupancy level. For each validation route, both the

position/orientation of each smartphone and the path traced through the shops/corridor are random. That is, the routes follow the predefined shops/corridor, but the movements inside these shops vary from one day to another.

Table 3. Smartphones employed in each validation route, days elapsed after the calibration phase, and occupancy level.

Days	Mall	Route	Smartphones	Occupancy
1	1	#1–#4	#1–#5	Low
4	1	#1–#4	#1–#5	Low
11	1	#1–#4	#1–#5	Low
11	1	#2–#3	#1–#5	High
18	1	#1–#4	#1–#5	Low
18	1	#2–#3	#1–#5	High
38	1	#1–#4	#1–#5	Low
74	1	#1–#4	#1–#10	Low
1	2	#1–#4	#1–#5	Low
4	2	#1–#4	#1–#5	Low
18	2	#1–#4	#1–#5	Low
60	2	#1–#4	#1–#5	Low
60	2	#1–#4	#1–#9	High

2.4. Wi-Fi Fingerprint Dataset Description

The complete dataset obtained from the Android calibration app and described in Section 2.1 employing the aforementioned *random walking survey method* has been uploaded to the Zenodo repository, managed by the European Organization for Nuclear Research (CERN). This repository was developed under the research project named Open Access Infrastructure for Research in Europe (OpenAire) funded by the European Commission. Currently, Zenodo contains a large number of datasets from heterogeneous research fields. The link to access our dataset can be found in [28].

In detail, our dataset is composed of 17,623 fingerprints acquired from five Android smartphones during the offline calibration phase for malls 1 and 2. These fingerprints are divided into 5084 from mall 1 and 12,539 from mall 2. Table 4 shows the different fingerprints acquired by each device, labeling the following aspects: (i) APs detected for each smartphone, (ii) the number of times that the RSSI was acquired, (iii) the number of scans performed, and (iv) APs per scan (on average).

Table 4. Offline calibration phase: summary of the fingerprints acquired in both malls using the five different smartphones.

Smartphone	Mall	APs Detected (2.4/5 GHz)	Scan Numbers	Average APs per Scan	RSSIs Acquired
#1	1	409/349	1033	49	50637
#2	1	462/398	2345	67	159290
#3	1	383/0	699	21	15185
#4	1	354/0	258	32	6934
#5	1	240/0	749	31	23816
#1	2	664/442	3600	41	150238
#2	2	746/462	6224	52	328355
#3	2	446/0	838	17	14569
#4	2	518/0	1064	22	24123
#5	2	359/0	813	30	24758

In relation to the validation routes, there were 100,732 validation fingerprints captured from 10 different smartphones; 60,028 validation fingerprints for mall 1 and 40,704 for mall 2. As we worked at the shop level, the total number of fingerprints (calibrating and validation) has been classified into 182 areas, 69 for mall 1 and 113 for mall 2. Concerning the number of APs detected, 885 APs were found in the calibration phase for mall 1 and 1291

for mall 2, whereas 1225 APs were detected in the validation phase for mall 1 and 1752 for mall 2. Compared to other references analyzed in the introduction section [16,24,25,27,45], this complete fingerprint information is one of the largest open access datasets available to the scientific community. In Appendix A, the content of each of the files that make up our dataset is detailed.

3. Results

We have evaluated and compared, in terms of stability over time, device heterogeneity, and the influence of occupancy on shop-level accuracy, different IPSs generated following the procedure depicted in Section 2.1.5 by means of the three indoor positioning algorithms: SVM, KNN, and Freeloc. They are described in Section 2.1.5. The evaluation was carried out in two malls, employing the validation routes and smartphones described in Section 2.3. To this end, we have generated five different IPSs with each algorithm using the labeled samples acquired in the offline calibration phase with each one of the #1–#5 smartphones. The validation routes were then processed with each of the IPSs generated, where the inputs are the fingerprint samples to be located, and as output, the placement where they were acquired is estimated. In our case, the output was a shop-level area where the samples were collected.

The performance metric employed to search for the best optimization value is the Euclidean distance from the centroid of the area estimated by the IPS to the centroid of the area labeled in the sample. In the case of a sample for which the target zone is correctly estimated, the Euclidean error is zero. Thus, the shorter the Euclidean distance, the better the performance of the IPS. Moreover, we have employed the cross-validation technique. This means that to verify the performance of the IPS generated from the fingerprints collected by smartphone #1, the validation routes obtained from this smartphone were discarded. This procedure was applied for the remaining smartphones.

The parameters to optimize each of the algorithms are different. In the case of KNN, these parameters are the number of neighbors (APs) employed and the value of the RSSI when an AP is not found in the Wi-Fi scan. In the case of Freeloc, the optimization parameters are the δ and RSS_{peak} [15] employed for the generation of the vector. RSS_{peak} is the RSSI value of the highest frequency during the measurement, while δ is a parameter that must be computed. Finally, in the case of SVM, the parameters are the kernel [17] employed as a classification function and the regularization values (coefficient assigned in the misclassification). For each of the offline fingerprints using smartphones #1–#5 in both malls, we carried out a sweep of the optimization parameters with the aim of finding those with better performance. We tested from 1 to 15 neighbors and 0, 100, and 200 as RSSI values when an AP is not found. In the case of Freeloc, we tested δ from 1 to 10 and RSS_{peak} from 0 to 16. Regarding SVM, we checked the following kernels: linear, poly, rbf, and sigmoid, with regularizations valued at 0.1, 1, 2, and 3. The values with the lowest errors for the KNN algorithm in both malls and for all the smartphones are three neighbors and 100 for the RSSI when there is no AP. Concerning Freeloc, the optimal values for δ and RSS_{peak} are shown in Table 5. Regarding the kernel and the regularization parameters for SVM, the optimal values are illustrated in Table 6.

In the rest of the section, we compare the IPSs generated by means of the three indoor positioning algorithms, KNN, Freeloc, and SVM, employing the parameters previously optimized, with the premises of stability over time, device heterogeneity, and the influence of occupancy rates.

Table 5. δ and RSS_{peak} optimal values for both malls and smartphones #1–#5.

Smartphone	Mall	δ	RSS_{peak}
#1	1	1	0
#2	1	1	2
#3	1	3	0
#4	1	1	0
#5	1	1	0
#1	2	1	1
#2	2	1	2
#3	2	1	0
#4	2	1	0
#5	2	1	0

Table 6. Kernel and regularization parameters which have the lowest Euclidean distance errors for SVM.

Smartphone	Mall	Kernel	Regularization Parameter
#1	1	rbf	3
#2	1	rbf	3
#3	1	sigmoid	3
#4	1	sigmoid	3
#5	1	sigmoid	3
#1	2	rbf	3
#2	2	sigmoid	3
#3	2	rbf	3
#4	2	rbf	3
#5	2	rbf	3

3.1. Variability of Performance over Time

To evaluate the three IPSs, the first comparison we conducted was to observe their evolution and performance over time. In works [12,46], they showed great variability with respect to the evolution of the Wi-Fi fingerprint in a large environment. This occurs because APs disappear and others appear. Since offline fingerprint acquisition is one of the most time-consuming tasks and is performed once every several months, the stability of the IPS as time goes by is one of the most important performance indicators. For this purpose, with the samples generated in the offline calibration phase, we generated five different IPSs for each mall with the samples from smartphones #1–#5, to later test the routes labeled #1–#4 over days 1–74 for mall 1, and days 1–60 for mall 2. As has been previously mentioned, we employed the cross-validation procedure and the Euclidean distance error calculated by the difference between shops estimated by the algorithms and the real labeled shop in the sample. The zero-error value is set when a sample is estimated in the area where it was acquired. The evolution of the IPS over time can be observed in Figure 6a for Freoloc, Figure 6b for KNN, and Figure 6c for SVM.

3.2. Heterogeneity Diversity Performance

As described in [10] and validated in Section 2.4, each smartphone, even those with the same chipset, obtains a very different fingerprint. That is, the data generated by each smartphone in the offline calibration phase differ in RSSI levels, scan rate, and the number of APs detected. Therefore, it is crucial to explore whether the IPS generated by a smartphone from the fingerprint samples gathered has similar accuracy. To this aim, we tested our IPS solution with the routes labeled #1–#4 generated by different devices on day 74 for mall 1 and day 60 for mall 2 after calibration. Note that these days are the last days with evaluation routes. As we have established, ten different smartphones were employed in the routes defined for mall 1 and nine for mall 2. With this process, we can find the indoor location algorithm which has the greatest accuracy regardless of the device

employed in the calibration procedure. The results are illustrated in Figure 7 (Freeloc), Figure 8 (KNN), and Figure 9 (SVM) by means of the cumulative distribution function (CDF) metric. CDF depicts the error (measured in meters) of the percentile of samples with a lower error than the indicated one on the x-axis. As in the rest of the Results section, the cross-validation procedure is employed with Euclidean distance as a metric error. In the CDF, the percentage of samples with 0 m errors is the percentage of samples which have successfully estimated the right shop.

Figure 6. Evolution of the mean error over the time for each of the smartphones in both malls with (a) Freeloc, (b) KNN, and (c) SVM.

3.3. Influence of Occupancy Rates

Another factor to be carefully considered is the influence of the fading caused by the number of people in the mall. It is well known that people's movements affect RSSI levels [11]. In a mall, occupancy ostensibly changes according to the day of the week or even the hour of the day. Typically, there are more people at the weekend or on holidays than on working days. As the calibration phase must not disturb the regular operation of the mall, we cannot control the number of visitors and their frequency. We have studied the performance of Freeloc, KNN, and SVM in terms of mall capacity by considering a single calibration carried out over a few hours.

Therefore, to test the influence of fading on the algorithms, several pre-established routes were followed on the same day but at different times. Specifically, we took routes #2 and #3 for mall 1 on days 11 and 18 after the calibration day, and routes #1 and #4 for mall 2 on day 74. In both malls, the process was completed in the morning when the number of visitors was small, and in the afternoon, when there was a larger number of potential clients. Results employing the CDF metric are illustrated in Figure 10a for Freeloc, Figure 10b for KNN, and Figure 10c for SVM.

3.4. Processing Time

Another interesting feature of the IPS involving scalability and the ability to precisely locate a large number of visitors is the processing time of the three different algorithms. To this end, we have evaluated the time employed in determining one of the validation routes generated. The time needed to generate the IPS has been ignored because it is carried out every few months and, therefore, does not affect the overall process. The most critical issue for the appropriate operation of the IPS is to compute the precise location of day-to-day visitors, which can be in the range of a few thousand. Processing time was measured on a PC with an AMD Ryzen 5 and 8 GB of RAM. We selected the route labeled #1, day 1 with smartphone #2, and employed the different IPSs (one per algorithm) generated with smartphone #1. It is a route with 701 fingerprint samples acquired over 1 h and 20 min. The processing time also includes all the routines/code to feed the IPS, like the database extraction of the validation route data, the computation time of the algorithm, and the time

spent saving the results in a database. Therefore, the processing time depicted in Table 7 is the amount of time required by the IPS module to compute a regular user visit for each one of the algorithms.

Table 7. Processing time for the Freoloc, KNN, and SVM for a validation route.

IPS	Time (s)
Freoloc	11.93
KNN	7.97
SVM	8.51

Figure 7. CDF referring to the accuracy of the IPS generated with Freoloc on day 74 for mall #1 and day 60 for mall #2 employing smartphones (a) #1, (b) #2, (c) #3, (d) #4, and (e) #5.

Figure 8. CDF referring to the accuracy of the IPS generated with KNN on day 74 for mall #1 and day 60 for mall #2 employing smartphones (a) #1, (b) #2, (c) #3, (d) #4, and (e) #5.

Figure 9. CDF referring to the accuracy of the IPS generated with SVM on day 74 for mall #1 and day 60 for mall #2 employing smartphones (a) #1, (b) #2, (c) #3, (d) #4, and (e) #5.

Figure 10. Influence of occupancy rates on the IPS generated with (a) Freeloc, (b) KNN, and (c) SVM.

4. Discussion

Figure 6 shows the evolution of the performance of the IPS generated by the three algorithms for both malls using smartphones #1–#5. In the case of Freoloc, the results illustrate a flat slope referring to the mean errors (in meters) as time passes, showing an error of around 5 m in the best case (smartphone #2 in mall 2) and 11 m in the worst case (smartphone #4 in mall 1). This means that for most of the IPSs generated using Freoloc, the performance of our IPS on day 74 for mall 1 and on day 60 for mall 2 (that is, the last day of measurement for each mall) is similar to the performance on day 1. In the cases of KNN and SVM, the slope of the mean errors increases as time passes for the entire IPS. Moreover, the mean values of the errors on day 1 for the best performance are, in both cases, around 10 m for smartphone #2 in mall 1. These values are worse than in the case of Freoloc. Therefore, we can conclude that in the case of Freoloc, the error does not increase as time goes by and the system is stable and robust over time. In contrast, in the cases of KNN and SVM, the errors increase over time for the five IPSs generated in both malls. Additionally, it should be noted that in the case of Freoloc, the engines generated for each smartphone in mall 2 present lower errors than the ones generated for mall 1, although mall 2 has a larger surface and a greater number of shops. This is due to the larger number of APs detected in mall 2, which involves a greater number of representative fingerprints for each area.

Regarding the results for device heterogeneity, Figure 7 (Freoloc), Figure 8 (KNN), and Figure 9 (SVM) illustrate the CDF outcomes of the last day of the validation routes for each mall/smartphones #1–#5. It is worth mentioning that errors valued at 0 m on the x-axis are the percentage of samples successfully determined on the right side of the y-axis. In the case of Freoloc, this percentage is around 60% for smartphone #1 and around 40% in the cases of smartphones #3, #4, and #5 (best cases). Concerning KNN, more irregular results are observed than in the case of Freoloc. Therefore, in all the IPSs generated using the five smartphones, the worst performance is around 10% of the samples determined correctly in the right zone. However, 90% of the samples are properly determined in the case of the IPS generated with smartphone #1 for the test device smartphone #2 in mall 2. Similar results can be found for SVM and the five IPSs generated, with values of 0 m errors from 5% to 80% in the case of smartphone #1. Another interesting result to analyze in the case of the CDF is the 80th and 90th percentile. These values illustrate the errors in 80% and 90% of the samples, respectively. In the case of Freoloc, the calculated CDFs show an error of around 30 m in the 80th percentile and 40 m in the 90th percentile, regardless of the smartphone used. It is worth mentioning that misclassification of a sample in our solution entails an error in meters from the centroid of an area to the centroid of another, and the larger the area with errors, the greater the distance of the error. In the case of KNN, the values obtained show a greater error than in the case of Freoloc, with an 80th percentile of around 60 m for smartphone #3 but very poor performance for smartphones #1, #2, #4, and #5. A similar result to that of KNN can be observed with SVM. The results show a similar percentile of error, regardless of the model of smartphone used in the calibration phase, only for the Freoloc algorithm. This demonstrates that any smartphone can perform the calibration process, resulting in a solution that is not dependent on hardware if this algorithm is employed in IPS generation.

With respect to the influence of occupancy levels, Figure 10 illustrates that there are no significant variations in the mean metric error between high and low occupancy once the validation routes have been executed. An exception is smartphone #3, which shows greater error in low occupancy than in high occupancy in samples below the 20 m percentile in both malls; however, for the percentile of distances greater than 30 m (x-axis), a similar error is attained. In the case of KNN, some differences can be found for all the smartphones in both malls and for low/high occupancy. The cases of smartphones #2 and #5 for mall 1 are remarkable as they present better accuracy with low occupancy. In the case of SVM, the most remarkable situation is with smartphone #2 for mall 2, with better results for high rather than low occupancy and without differences in high/low occupancy in other

scenarios. Therefore, we can conclude that the IPSs generated by the three algorithms are not affected by occupancy rates.

Finally, the values obtained for the processing time of a route simulating a 1 h 20 min visit to the mall show the worst results in the case of Freeloc, at 11.93 s. In the case of KNN, the processing time is 7.97 s, and for SVM, 8.51 s. As previously mentioned, the computing of the validation route was performed in a non-optimized final user PC, not in a specific computing server. This means that processing times can be drastically reduced. It should be kept in mind that localizing a few thousand users per day is an excellent result in terms of the mean value of numbers of visitors in a large mall. We can conclude that the three algorithms are scalable from a processing time perspective.

In summary, IPS solutions implementing Freeloc have better performance as time passes and in comparison with KNN and SVM, regardless of the type of device used. In terms of occupancy levels, the results show similar accuracy no matter the location algorithm employed. Finally, keeping processing time in mind, the best results are for KNN, although SVM and Freeloc do not show significant differences.

5. Conclusions

In this work, a complete contextual marketing platform including the capacity to automatize marketing campaigns, merging online and offline customer behavior, is proposed. The purpose of the system is achieved with a scalable and straightforward Wi-Fi-based indoor positioning system (IPS) at the shop level. Concerning the generation phases of the IPS, one of the most important challenges of the deployment of our IPS-based solution, the fingerprint calibration phase, has been designed and developed using the (i) *random walking survey* method, (ii) an easy-to-use ad hoc Android app, and (iii) a tool based on Jineditor to generate digital maps of the malls. This combination of technologies and procedures could allow us to extend our system to any mall by simply employing the existing APs for connectivity purposes.

Regarding IPS performance, three different indoor positioning algorithms, Freeloc, KNN, and SVM, have been evaluated and compared under the premises of only using Wi-Fi fingerprints as input parameters and without adding new hardware. Regardless of the smartphone employed in the calibration phase, it has been demonstrated that Freeloc has enough accuracy and stability to be employed as a KPI provider in a marketing campaign. Moreover, our solution has been validated under different occupancy scenarios, demonstrating its feasibility as time passes. The performance of our solution remains stable during a substantial time period, with occupancy levels not affecting the results.

The Wi-Fi fingerprint dataset is open access and was generated by means of 10 different smartphones over several weeks in two malls. Furthermore, our dataset provides the RSSI data of movement in shops/corridors of two malls, simulating the movement of visitors during a shopping trip.

Finally, as future work, the implementation of some preprocessing techniques related to calibration fingerprints together with the enforcement of realistic movement models between shops/corridors, such as the hidden Markov model, could improve the performance of the system without increasing computational requirements. Furthermore, thorough studies to discern the preferences of customers split into age groups as well as by their location privacy should be included in future studies.

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Appendix A. Structure of the Files within the Dataset

The dataset is made up of eight “.csv” files that can be downloaded and employed without any specific software. The content of each file is described as follows:

- “building.csv”: two registers with the ID of mall 1 and mall 2.
- “floor.csv”: there is an input for each of the floors of the two malls.
- “zones.csv”: for each zone, the mall and the floor in the mall are indicated.
- “training.csv”: in this file are registered the IDs and the description of the five different calibrations performed (one per smartphone) in each of the malls.
- “training_sample.csv”: each file is an RSSI in dBm recorded during the offline calibration phase. The timestamp, channel, and MAC of the AP are also stored.
- “route.csv”: the IDs and the description of the validation routes are indicated in this file.
- “route_sample.csv”: with a similar structure to training_sample.csv, the RSSIs acquired during the validation routes are stored in this file.
- “euclidean_distance.csv”: with the aim of evaluating the error of the different algorithms, this file records the Euclidean distance from the center of a shop to the others in meters.

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Capítulo 3

Resumen de los artículos

3.1 A Hybrid Analog-Digital Processing System for Amplitude-Monopulse RSSI-Based MiMo WiFi Direction-of-Arrival Estimation

3.1.1 Breve introducción

Este trabajo, publicado en la revista *Journal of Selected Topics in Signal Processing* en el año 2018, se centra en el diseño, implementación y demostración de la viabilidad de un sistema híbrido analógico-digital (HAD) WiFi de bajo coste, basado en hardware comercial, que permita detectar el ángulo (DoA) de la señal proveniente de un dispositivo IoT empleando técnicas Radar monopulso empleando la amplitud de la señal recibida. Una de las principales características del sistema generado es que para el cálculo del ángulo no se emplea la componente compleja de una señal RF sino que se basa solamente en una componente digital de la señal como es la RSSI. El sistema generado emplea dos antenas directivas con una inclinación determinada que varía en función del tamaño de las mismas. Esto es lo que se conoce como configuración monopulso. Esta disposición de las antenas, junto con el empleo de una tarjeta MiMo WiFi que permite leer de modo independiente la RSSI de la señal recibida en cada una de las antenas, permite aplicar la técnica Radar Monopulso. Al emplear la componente compleja de la señal y requerir solamente la RSSI, el procesamiento de la señal que se necesita realizar para estimar el DoA es de baja complejidad, siendo capaz el sistema de estimar el DoA con facilidad y en tiempo real. En la Figura 3 se muestra el esquema global del dispositivo desarrollado.

Figura 3. Esquema del sistema monopulso MiMo HAD

3.1.2 Metodología

La sucesión de tareas que se han llevado a cabo para la obtención de los resultados y la posterior redacción del artículo se describen a continuación:

- Fase inicial de búsqueda y estudio de la literatura de sistemas de localización previos basados en DoA como Music [23] o ESPRIT [24].
- Búsqueda, estudio y compra de los diferentes materiales comerciales que forman el sistema HAD de adquisición de RSSI, incluyendo las antenas directivas, el chipset MiMo y la placa base de adquisición de datos.
- Desarrollo del software que permite la lectura y cuantificación simultánea de las RSSI de cada una de las dos antenas directivas y su posterior envío a un servidor donde se realiza el procesamiento.
- Se definió entonces la función monopulso digital basada en la amplitud como el cociente de la diferencia y la suma de las señales RSSI (1).

$$\Psi_{RF}(\theta) = \frac{\Delta_{RF}(\theta)}{\Sigma_{RF}(\theta)} = \frac{P_{RF1}(\theta) - K_{RF} \cdot P_{RF2}(\theta)}{P_{RF1}(\theta) + K_{RF} \cdot P_{RF2}(\theta)} \quad (1)$$

- Posteriormente se realizó el estudio teórico de los elementos que intervienen en la función monopulso como son: la cuantificación del error y el factor de corrección (K_D).
- Estudio teórico y demostración práctica en un entorno controlado, como es la cámara anecoica de la ETSIT, de la determinación del DoA del sistema frente a cambios de distancia. También se estudió el efecto multipath producido tanto por el suelo como por las paredes, empleando para ello planchas metálicas.
- A continuación, se llevó a cabo una demostración del funcionamiento del sistema completo empleando dos dispositivos HAD en campo abierto. Para ello se usó un smartphone a modo de dispositivo IoT.
- Por último, se realizó una comparación en términos de complejidad y error angular frente al resto de sistemas DoA que se enumeran en la bibliografía.

3.1.3 Resultados

El primer resultado destacado de este trabajo es la comprobación de que la función monopulso obtenida de forma teórica se corresponde a la función monopulso obtenida en cámara anecoica, tanto en el ámbito analógico como en el ámbito digital. Para llevar a cabo la medición de la potencia en analógico se empleó un analizador de espectro vectorial (VNA) y para la medición en el ámbito digital se usó el propio dispositivo HAD implementado. Además, se obtuvo un field of view (FoV) o rango de funcionamiento del dispositivo de $\pm 30^\circ$. En la Figura 4 se muestra la representación de las funciones monopulso obtenidas junto con el FOV obtenido.

Con respecto al comportamiento de la función monopulso ante el *multipath* producido por el suelo o por las paredes laterales, se comprobó que no se producen variaciones en el resultado del DoA estimado ante la presencia de estos tipos de *multipath*. Esto es debido a que las variaciones producidas por la RSSI son absorbidas por ambas antenas simultáneamente, haciendo que la función monopulso permanezca invariante.

Además, se estudió el comportamiento de la función monopulso ante las variaciones producidas por los movimientos de las personas. Para ello, se realizó un estudio de la variación de la función monopulso cuando el teléfono es introducido en un bolsillo, se sitúa el teléfono en posición de llamada junto a la cabeza de una persona y cuando se establece el teléfono en la posición de escritura. Se observó, de nuevo, que las variaciones de la RSSI eran absorbidas de forma simultánea por las dos antenas y que, por lo tanto, la función monopulso permanecía invariante.

Figura 4. Función monopulso teórica, analógica y digital

Por último, mediante el empleo de dos dispositivos HAD se realizó en campo abierto un experimento con el fin de realizar una estimación de la posición (x,y) empleando para ello el DoA estimado de forma independiente por cada uno de los dispositivos. En la Figura 5 se muestra la distribución espacial de los dispositivos (Izq) y los resultados obtenidos (Dcha). Se puede apreciar que la posición (x,y) estimada como el punto de corte de los dos ángulos determinados por cada uno de los dispositivos se aproxima a la posición original del smartphone, presentando un error de unos pocos decímetros.

Figura 5.Izq) Disposición de los dispositivos HAD para estimación (x,y). Dcha) Resultados obtenidos

3.1.4 Conclusiones y contribución.

La principal contribución de este trabajo es demostrar, mediante una implementación real, la viabilidad de emplear la técnica Radar Monopulso para

generar un sistema de localización basado en DoA empleando un sistema HAD diseñado e implementado mediante hardware comercial gracias a una tarjeta MiMo WiFi en la banda de 2.4 GHz. Además, las técnicas de procesamiento de señal, tanto en el ámbito analógico como digital, son de escasa complejidad, pudiéndose localizar varios dispositivos de forma simultánea y en tiempo real.

El sistema de localización generado presenta una precisión similar a otros dispositivos de localización basados en WiFi que se han encontrado en la bibliografía, pero requiere de una menor complejidad para su operativa. En la Tabla 1 se muestra la comparativa con otros algoritmos de localización en términos de precisión y de complejidad.

Tabla 1. Comparación entre el sistema propuesto y otras plataformas de localización basadas en WiFi.

REF	Arquitectura	Precisión	Nivel de complejidad
[16], [28], [29]	Sistemas basados únicamente en RSSI fingerprinting	Metros en interior	Media. La adquisición de RSSI es simple, pero se requiere de una fase exhaustiva de adquisición de datos y posterior entrenamiento del algoritmo de clasificación.
[22], [30]	Técnicas basadas en CSI y <i>phased-antenna</i> para estimar el DOA	Centímetros en interior	Alta. Se requiere información de fase (CSI). Requiere modificaciones de hardware y de software para una medición precisa del retraso en fase de la señal.
[31]	Algoritmo MUSIC con CIS para estimación de DoA y ToF	Decímetros en interior	Alta. Se requiere información de fase (CSI) y el empleo del algoritmo MUSIC para la estimación del ToF y del DoA.
[32], [33]	Sistema basado en <i>fingerprinting</i> CFR	Centímetros en interior	Alta. Se requiere del <i>Channel Frequency Response</i> (CFR). Además, se requiere de una fase exhaustiva de adquisición de datos y posterior entrenamiento del algoritmo de clasificación.
Este trabajo	Estimación de DoA empleando técnicas monopulso	Decímetros en exterior	Baja. La adquisición de RSSI es sencilla. No se requiere de fase exhaustiva de calibración ni adquisición de datos ni algoritmo de clasificación, solamente se tiene que calcular el factor de corrección.

3.2 Near-Field Monopulse DoA Estimation for Angle-Sensitive Proximity WiFi Readers

3.2.1 Breve introducción

Este trabajo, publicado en la revista *IEEE Access* en el año 2019, supone una continuación del trabajo [1] en cuanto al empleo del *sniffer* HAD y de la función monopulso empleando señales WiFi se refiere. A diferencia del anterior, el estudio se centra en la implementación de la función monopulso para la generación de sistemas de localización en entornos de proximidad (menos de 5 metros). Se trata de una aplicación de los sistemas de localización para entornos donde las distancias son cortas, como, por ejemplo, detección de ángulo de aproximación de un objeto en edificios inteligentes o detección de dos dispositivos IoT que se encuentren a corta distancia.

Para la realización del trabajo se emplearon de nuevo las mismas antenas directivas del trabajo anterior, empleando la misma configuración monopulso con un ángulo de inclinación de 7° . De acuerdo a la teoría de antenas, se conoce que los diagramas de radiación se comportan de manera diferente en función de la distancia y que se forman tres regiones características: la región de Rayleigh o *reactive near-field*, la región de Fresnel o *radiative near-field*, y la región de Fraunhofer o *far-field*. Estas regiones se forman a una distancia de la antena que varía en función del tamaño de la misma y la longitud de onda de la señal RF. Para nuestro sistema de antenas, con un tamaño de 45 cm. y una longitud de onda de 12.24 cm., la región de *far-field* comienza a 3.3 metros y la separación entre las regiones de *near-field* se encuentra a 55 cm.

Debido a que los diagramas de radiación de las antenas cambian a lo largo de cada una de las regiones, la función monopulso, entendida como el cociente del diagrama diferencia y el diagrama suma, cambia también función de la distancia. Estos cambios en la función monopulso en base a la distancia, que afectan al error angular del sistema, son analizados en profundidad a lo largo del artículo.

3.2.2 Metodología

A continuación, se desglosan las actividades que se han realizado para llevar a cabo los trabajos que dieron lugar a este artículo:

- Cálculo de las distancias que forman las diferentes regiones de *far-field* y *near-field* en función de las antenas empleadas y la longitud de onda.
- Estudio teórico de los diferentes diagramas de radiación, así como los diagramas suma, diferencia y la función monopulso en función de la distancia.

- Comprobación de los estudios teóricos empleando un dispositivo real en un entorno controlado como es la cámara anecoica de la ETSIT.
- Estudio del error de estimación del DoA en función de la función monopulso empleada en base a la distancia.
- Estimación del DoA de un dispositivo real en base a la distancia empleando la función monopulso apropiada.

3.2.3 Resultados

El primero de los resultados que se obtuvieron en este trabajo fueron los estudios teóricos de la variación de los diagramas suma (Σ) y diferencia (Δ), así como las funciones monopulso para las distancias $r=3, 2, 1, 0.5$ y 0.25 m. Se puede observar en Figura 6 Izq las diferencias en los diagramas Σ y Δ en función de la distancia obtenidos teóricamente, lo que provoca la diferente inclinación de la función monopulso, mostrado en la Figura 6 Dcha.

Figura 6. Izq) Diagramas Σ y Δ teóricos normalizados en función de la distancia ($r=3, 2, 1, 0.5$ y 0.25 m). Dcha) Funciones monopulso estimadas teóricamente en función del ángulo y la distancia.

Los resultados teóricos obtenidos anteriormente son confirmados en un experimento realizado en la cámara anecoica de la ETSIT. Para ello se situó el dispositivo IoT a las distancias de $r=3, 2, 1, 0.5$ y 0.25 metros y se realizó una medición de 100 muestras RSSI para cada uno de los ángulos. El resultado de representar los diagramas Σ y Δ de la media de las 100 medidas es representado en la Figura 7 Izq., mientras que las funciones monopulso generadas es representada en la Figura 7 Dcha. Se puede observar la similitud de los diagramas obtenidos de forma teórica representados en la figura anterior y los obtenidos experimentalmente.

Figura 7. Izq) Diagramas Σ y Δ medidos en cámara anecoica en función de la distancia ($r = 3, 2, 1, 0.5$ y 0.25 m). Dcha) Funciones monopulso estimadas teóricamente en función del ángulo y la distancia.

De las funciones monopulso obtenidas para las diferentes distancias, es fácil comprender como en el caso de estar a una determinada distancia y usar una función monopulso que no corresponde a esa distancia, se obtiene un mayor error angular que en el caso de emplear la función monopulso apropiada. Esta afirmación fue comprobada mediante dos experimentos empleando tres dispositivos diferentes: un AP y dos smartphones. En el primero de los experimentos se situó el AP y los smartphones a una distancia de 50 cm., adquiriendo la RSSI a diferentes ángulos dentro del FoV. En el segundo experimento la distancia del dispositivo al AP y a los smartphones fue de 1 m. La configuración del experimento se muestra en la Figura 8.

Figura 8. Fotografía de la distribución del experimento para el cálculo del DOA empleando la función monopulso en función de la distancia

Para la prueba a 50 cm de distancia, se comprueba que en el caso de emplear la función monopulso apropiada a esa distancia, el RMSE es de 3.1 cm., 1.8 cm. y 3.8 cm. para cada uno de los dispositivos, mientras que en el caso de emplear la función monopulso correspondiente a una distancia de 2 m. se tiene errores de hasta 52 cm. De forma similar, para el experimento 2, en el caso de usar la función monopulso apropiada, la de 1 m. en este caso, el RMSE de los errores son de 4.4 cm, 5.1 cm y 6.7 cm. respectivamente para cada dispositivo. Por el contrario, si se emplea la función monopulso correspondiente a 2 metros se obtienen errores de hasta 38 cm. Los resultados completos de este experimento se muestran en Tabla 2

Tabla 2. RMSE en cm. para cada dispositivo empleando la función monopulso de $H=2m$, $H=1m$ y $H=50cm$

Función monopulso empleada para el cálculo del DOA	Distancia $H = 50 \text{ cm}$		
	AP	Teléfono 1	Teléfono 2
$\Psi(x, H=2m)$	57.0 cm	52.9 cm	49.2 cm
$\Psi(x, H=1m)$	18.5 cm	17.9 cm	16.1 cm
$\Psi(x, H=50cm)$	3.1 cm	1.8 cm	3.8 cm
Función monopulso empleada para el cálculo del DOA	Distancia $H = 1 \text{ m}$		
	AP	Teléfono 1	Teléfono 2
$\Psi(x, H=2m)$	31.9 cm	38.1 cm	27.3 cm
$\Psi(x, H=1m)$	4.4 cm	5.1 cm	6.7 cm
$\Psi(x, H=50cm)$	17.9 cm	17.0 cm	19.9 cm

3.2.4 Conclusiones y contribución

La principal conclusión y contribución de este trabajo ha sido demostrar que la función monopulso se puede emplear como solución para la implementación de sistemas de localización de dispositivos WiFi de proximidad. Se trata de un ámbito de actuación en la que suelen destacar los sistemas basados en otras tecnologías como RFID o UWB, pero que, debido a que la tecnología WiFi se encuentra ampliamente extendida y presente en multitud de dispositivos IoT, son muchas las aplicaciones que se pueden beneficiar de esta tecnología.

Se debe de tener en cuenta que al producirse variaciones en la función monopulso debido a la distancia, se tiene que seleccionar la función monopulso apropiada para la estimación del DoA. Tal y como se muestra en la Tabla 2, o se escoge la función monopulso determinada para la distancia a la que se encuentra el dispositivo a localizar, o el error angular se ve incrementado.

Por último, destacar que se trata de la primera vez que un sistema de estimación de DoA basado en la función monopulso empleando la amplitud de la señal recibida es empleado para técnicas de detección angular en proximidad. Tal y como se muestra en Tabla 3, la región de campo cercano de la mayoría de sistemas monopulso RF/WiFi que se pueden encontrar en la bibliografía se extienden a unas distancias donde los efectos del campo cercano no pueden ser ignorados.

Pero como se puede intuir, este trabajo tiene la limitación de que es necesario conocer la distancia hasta el dispositivo a localizar de antemano para poder aplicar la función monopulso apropiada. Esta limitación provoca el origen del siguiente trabajo que detallaremos a continuación.

Capítulo 3: Resumen de los artículos

Tabla 3. Distancias de funcionamiento de sistemas monopulso empleados en IoT

Ref.	Frecuencia	Tamaño de array monopulso S	$d_{\text{NEARFIELD}}$ (1)	d_{FARFIELD} (2)	FoV
[34]	867 MHz	54 cm	42 cm	1.7 m	$\pm 40^\circ$
[35]	915 MHz	37 cm	24 cm	83 cm	$\pm 30^\circ$
[36]	920 MHz	18 cm	8 cm	20 cm	$\pm 20^\circ$
[37]	868 MHz	60 cm	49 cm	2 m	$\pm 40^\circ$
[38]	2.3 GHz	30 cm	28 cm	1.3 m	$\pm 45^\circ$
[39]	2.45 GHz	9 cm	5 cm	14 cm	$\pm 45^\circ$
[40]	2.45 GHz	30 cm	30 cm	1.5 m	$\pm 40^\circ$
[1]	2.45 GHz	45 cm	50 cm	3.3 m	$\pm 30^\circ$

3.3 Wi-Fi RTT-Based Active Monopulse RADAR for Single Access Point Localization

3.3.1 Breve introducción

Como se ha comentado en nuestro trabajo anterior [2], para la aplicación de la función monopulso apropiada a la distancia del dispositivo IoT que se desea localizar, es necesario conocer previamente esta distancia, con lo que el número de aplicaciones de este tipo de sistemas es limitado. Con el fin de solventar dicho hándicap se desarrolló este novedoso trabajo [3], publicado en la revista *IEEE Access* en el año 2021. En él se combina la estimación de DoA mediante la función monopulso de señales WiFi basada en amplitud con el estándar 802.11mc *Fine Time Measurement (FTM) Round Trip Time (RTT)* que nos permite calcular la distancia al dispositivo. Por lo tanto, se trata de una combinación de un sistema DoA como es la función monopulso, con un sistema ToA (Time of Arrival) como es FTM. Mediante la combinación de estas dos tecnologías, empleando un único AP somos capaces de determinar la posición exacta (x,y) gracias a que se puede determinar el DoA y la distancia de forma simultánea.

El protocolo 802.11mc [41] ha sido adoptado recientemente por Android e implementado en diversos smartphones que implementan este sistema operativo a partir de su versión 10 [42]. Se presenta como una evolución dentro de los sistemas de localización ya que, en teoría, nos ofrecerá una métrica más precisa que la RSSI. Mediante la combinación de tres APs que ofrezcan RTT y empleando técnicas de trilateración se puede conocer la posición exacta del dispositivo. Pero en nuestro caso, mediante la combinación de RSSI y RTT somos capaces de conocer la posición exacta empleando 1 único AP. Un esquema del sistema implementado se muestra en la Figura 9. Posteriormente se describe la metodología seguida, resultados obtenidos y las contribuciones de este trabajo.

Figura 9. Sistema Radar monopulso 2D implementado

3.3.2 Metodología

Se describen a continuación la sucesión de tareas que se han llevado a cabo para la realización de este trabajo:

- Implementación de una app Android que permite obtener la distancia a un AP empleando RTT y capaz de enviar dicho valor mediante MQTT al AP Yocto Wild.
- Modificación del AP Yocto Wild para ser capaz de leer de forma simultánea la RSSI proveniente de dos antenas directivas y añadirle la distancia proveniente de RTT enviada por el smartphone.
- Implementación de sistema de envío de datos desde el AP Yocto y su recepción en servidor de procesamiento.
- Caracterización de la métrica RTT en función de la distancia y del ángulo de lectura en cámara anecoica.
- Obtención de las funciones monopulso en base a la distancia para el dispositivo Yocto Wild y las antenas directivas empleadas.
- Estudio del error, tanto el error angular como el error de ranging, obtenido en cámara anecoica en función de la distancia y del ángulo.
- Experimento en patio de la ETSIT de la determinación de posición (x,y) en un *grid* de 12x12 metros y un total de 304 puntos empleando de forma simultánea las métricas RSSI y RTT.
- Representación del error angular, error de *ranging* y error de la distancia Euclídea de cada uno de los puntos del *grid*.

3.3.3 Resultados

El primero de los resultados que se obtuvieron fue la caracterización de la RTT en base a la distancia y al ángulo. Dado que se trata de un sistema conjunto de estimación de DoA y de estimación de distancia, se requiere de un primer proceso de análisis del comportamiento de la métrica de distancia (RTT) en función del ángulo. Además, se tiene que comprobar si el comportamiento varía en función de la distancia. Para ello se realizaron medidas de RTT desde -80° hasta 80° y a 3, 2, 1 y 0.5 metros. En la Figura 10 se puede observar el resultado de estas mediciones. Tal y como se esperaba, fuera del FoV de las antenas, que recordemos cubría la región de $\pm 30^\circ$, se puede observar que el error de RTT aumenta. Esto se debe a que la ganancia de las antenas disminuye fuera de esa región, y por lo tanto la calidad de la señal, provocando errores en el cálculo de la RTT. Este resultado se muestra en la Figura 10. Además, destacar que se tuvo que aplicar un *offset* de 600mm. provocado por el AP. El *offset* se mantiene estable en 600mm para todas las distancias y para todos los ángulos.

Figura 10. RTT obtenida para las distancias 3, 2, 1 y 0.5 metros desde -80° hasta 80°

Posteriormente se obtuvieron los diagramas de radiación y las funciones monopulso para cada una de las distancias. Tal y como se esperaba, para cada una de las distancias la pendiente de la función monopulso es distinta, pero al contrario que ocurría en el trabajo anterior, ahora somos capaces de obtener la distancia al objeto a localizar y aplicar la función monopulso correspondiente. El resultado de los diagramas Σ y Δ , junto con las funciones monopulso se muestra en la Figura 11.

Figura 11. Diagramas de radiación y funciones monopulso obtenidas

Finalmente, para comprobar el funcionamiento del sistema en un entorno real, se realizó el experimento en el patio de la ETSIT. Para ello se tomaron medidas simultáneas de la RSSI por cada una de las antenas y de la RTT en 304 puntos situados en un *grid* de 12x12 metros. Para cada uno de los puntos se obtuvo el error angular obtenido por la función monopulso según el RSSI obtenido. Se obtuvo también el error producido por RTT. Por último, se obtuvo el error con respecto de la posición (x,y) empleando el error según la distancia Euclídea respecto de la posición real del punto con respecto de la posición estimada según el DoA y la RTT. Tanto el *setup* del experimento, incluyendo la representación del FoV y las distancias radiales de 3, 2, 1 y 0.5 m., así como el mapa de calor de los errores para cada uno de los puntos del *grid* se muestra en la Figura 12. Se puede observar como los errores, sobre todo del DoA calculados mediante la función monopulso, se incrementan fuera del FoV. Esto es esperado ya que la función monopulso solo puede ser computada dentro del FoV dado que es la única zona donde presenta valores unívocos.

Figura 12. *Setup* del experimento y mapas de calor del error angular, error de ranging y error en distancia Euclídea

3.3.4 Conclusiones y contribución

Se trata del primer trabajo que ha implementado con éxito un sistema de localización de dispositivos IoT empleando un único AP mediante la combinación de la función monopolso WiFi basada en amplitud y el protocolo 802.11mc FTM-RTT. Mediante la función monopolso se computa el DoA mientras que mediante RTT se conoce la distancia al dispositivo. Gracias a la combinación de las dos técnicas se puede estimar la posición (x,y) exacta. Mediante este dispositivo se consigue ampliar el rango de aplicación del sistema dado que no se requiere conocer de antemano la distancia hasta el dispositivo a localizar. Además, el sistema de localización se implementa empleando un único punto de acceso WiFi.

El sistema propuesto tiene una menor complejidad de implementación que el resto de sistemas de localización basados en un único AP que podemos encontrar en la bibliografía. Esto se debe a que los sistemas de este tipo requieren de acceder a información compleja de la señal, como los basados en CSI, o bien requieren de un tipo de antenas específicas. Además, nuestro sistema tiene una precisión similar, o incluso mejor, que el resto de sistemas analizados en la bibliografía. En la Tabla 4 se muestra la comparativa frente al resto de sistemas de localización que emplean un único AP.

Tabla 4. Comparativo del sistema implementado frente a otro tipo de sistemas de un solo AP

	Características principales	Problemas	Error medio
Cupid [43]	Determinación simultánea de ranging y DoA calculado mediante CSI y sensores inerciales del smartphone.	El dispositivo a localizar debe de estar dotado de sensores inerciales	En torno a 5 m
Sail [44]	Solución ToF que emplea el CIR de capa física y el reloj interno de las tarjetas WiFi.	Requiere que el reloj interno de las tarjetas WiFi tenga una alta precisión, lo que no ocurre en todas las tarjetas comerciales.	2.5 m
Chronos [45]	ToF obtenido de CSI empleando salto en frecuencia a lo largo de 35 canales WiFi.	Es necesario modificar los drivers de las tarjetas WiFi dado que el salto en frecuencia no está implementado en el estándar	Decímetros en LoS
S-Phaser [46]	Sistema de <i>ranging</i> empleando CSI con salto en frecuencia de dos canales WiFi y tres antenas MIMO para realizar triangulación	Es necesario modificar los drivers de las tarjetas WiFi dado que el salto en frecuencia no está implementado en el estándar	1.5 m en LoS
SiFi [47]	Sistema ToF de triangulación basado en CSI empleando en 3 antenas MIMO separadas del AP unos pocos metros	No puede ser empleado en tiempo real debido a la alta complejidad	0.93 m
Splicer [48]	<i>Power delay profiling</i> con un mecanismo de corrección de errores producidos por el hardware	Es necesario modificar los drivers de las tarjetas WiFi dado que el salto en frecuencia no está implementado en el estándar	1 m
[49]	<i>Switched Beam Antenna</i> con ocho antenas directivas	Emplea un sistema complejo de antenas que debe de ser controladas electrónicamente	0.95 m en cámara anecoica
[50]	Emplea datos RSSI provenientes de bluetooth y datos de sensores de movimiento	El dispositivo a localizar debe tener sensores inerciales	5.6 m
Este trabajo	Radar 2D con RTT y un sistema monopulso basado en RSSI	Se tiene un FoV de solo 60°	0,95 m

3.4 Wi-Fi Direction Finding with Frequency-Scanned Antenna and Channel-Hopping Scheme

3.4.1 Breve introducción

En los trabajos anteriores [1]–[3] se ha empleado el mismo sniffer HAD con antenas de panel directivas para la generación del sistema de localización. Como se comentaba en dichos trabajos, mediante los diagramas Σ y Δ se obtiene la función monopolso que solamente es unívoca desde -30° hasta 30° . Por lo tanto, la combinación empleada de sniffer-antenas directivas de panel tiene un FoV de 60° , siendo este una de las principales limitaciones del sistema. Fruto de esta limitación, se realizó este nuevo trabajo [6] que fue publicado en IEEE Access en el año 2021. Pero la ampliación del FoV no se puede hacer a toda costa, sino que el trabajo se ha realizado siguiendo la misma filosofía de tener un procesamiento de señal simple, por lo que se sigue empleando como input del sistema solamente la RSSI obtenida del dispositivo que se desea localizar, evitando así el uso de la componente compleja de la señal.

Para ampliar el FoV se han realizado dos cambios fundamentales con respecto a los trabajos anteriores. Por un lado, se han sustituidos las dos antenas de panel directivas por una antena con dos puertos y con el mecanismo de escaneo de haz en frecuencia (*frequency-beam scanning antenna - FSA*). Estas antenas tienen la característica fundamental de que varían el haz de radiación dependiendo de la frecuencia a la que son estimuladas. En la Figura 13 se observa este comportamiento, donde se muestran los diferentes patrones de haz medidos en cámara anecoica para los canales WiFi 1, 6 y 11. Por otro lado, se ha implementado en el *sniffer* la técnica de salto en frecuencia (*channel-hopping*), que varía los canales WiFi del AP de forma dinámica. De este modo se puede variar la frecuencia a la que se estimula la antena.

Figura 13. Diferentes patrones de haz medidos en la cámara anecoica para diferentes frecuencias

Mediante el dispositivo descrito, empleando los 11 canales WiFi, se obtiene un vector característico para cada ángulo con 22 componentes. Este vector es empleado para generar los *steering vectors* que se emplean en el algoritmo MUSIC [23] para calcular el *pseudo-espectro*, y a partir de él estimar el DoA.

3.4.2 Metodología

- Diseño y fabricación de la antena con mecanismo de haz en frecuencia adaptada para los 11 canales de WiFi 2.4GHz
- Modificación del software que permite la implementación del sniffer con el mecanismo de salto en frecuencia entre los 11 canales WiFi y la lectura de las dos RSSI de forma simultánea.
- Caracterización del dispositivo, tanto en analógico con VNA (Analizador Vectorial de Espectro) como en digital mediante el propio *sniffer* empleando RSSI.
- Obtención de los *steering vectors* empleados en MUSIC para la generación del *pseudo-espectro* en cámara anecoica.
- Evaluación del rendimiento del sistema en un entorno real obteniendo el DoA de la señal y el error angular.
- Comparativa del rendimiento del sistema generado con respecto a otros trabajos que se pueden encontrar en la bibliografía.

3.4.3 Resultados

El primero de los resultados a destacar es la obtención de los *steering-vector* que se emplean en el cálculo del *pseudo-spectro* de MUSIC mediante el dispositivo propuesto en cámara anecoica. Dicho *pseudo-spectro* presenta un pico característico para el DoA de la señal del dispositivo IoT que se desea localizar. Al tener 11 canales WiFi en una antena con 2 puertos, se tienen 22 elementos para generar el *steering vector*. En la Figura 14 se muestran los *steering-vector* generados en cámara anecoica para -60° , 0° y 60° , así como los *pseudo-espectros* característicos generados. Como podemos observar, a diferencia de los trabajos anteriores, la calibración no se realiza obteniendo los diagramas de propagación y calculando la función monopoluso. Ahora se tiene que adquirir una sucesión de RSSIs para cada uno de los ángulos y para cada uno de los canales, obteniendo así un *steering-vector* de 22 componentes diferentes para cada uno de los ángulos.

Una vez realizada la calibración, se realizó un experimento para comprobar el funcionamiento del sistema en un entorno real. Para ello se empleó uno de los pasillos de la ETSIT de la UPCT. Para la generación de los vectores en este entorno se emplean 100 muestras en cada uno de los canales, tomando una muestra cada milisegundo y realizando una media de la RSSI adquirida. Por lo tanto, se tarda 100 msg. para la generación de vector completo. Se detectó que en los primeros 20 msg. de cada salto en frecuencia, la RSSI presentaba unas variaciones anormales cuya procedencia se desconoce. Probablemente sean producidas por el tiempo que tarda el dispositivo IoT en cambiar al nuevo canal detectado. Además de tener en cuenta este fenómeno, también se estudió el uso de 3, 6 o 11 canales WiFi. El objetivo era conocer si el error del DoA variaba con el número de canales empleados, dado que, si no varía, cuantos

menos canales se empleen mejor será el rendimiento del sistema. Esto es debido a que el tiempo de procesamiento en realizar el *channel-hopping* es menor si se tiene que realizar las variaciones en frecuencia entre 3 canales que entre 6 u 11 canales. Los resultados obtenidos se muestran en la Figura 15, donde se observa que el RMSE del DoA obtenido decrece a medida que se emplean más canales WiFi, al igual que decrece sino se emplea en el cálculo de los vectores los primeros 20 msg. Además, se puede observar como el error angular es menor en los ángulos donde el dispositivo que se desea localizar se encuentra perpendicular a la antena, es decir, en 0° .

Figura 14. Izq) Steering-vector generados para a) -60° , b) 0° y c) $+60^\circ$. Dcha) Pseudo-spectro generado por MUSIC a partir de los steering-vector para a) -60° , b) 0° y c) 60° .

Figura 15. RMSE durante los 180 para a) N=3, b) N=6 y c) N=11 canales

En la Tabla 5 se muestra empleando el RMSE del error angular y con valores numéricos como el error disminuye a medida que se aumentan los canales WiFi (N=3, N=6 y N=11), obteniendo un RMSE de 7.1° para 11 canales y 0°.

Tabla 5. RMSE del error angular sobre la estimación del DoA para diferentes canales WiFi.

FoV	N= 3	N = 6	N = 11
45°	14.1°	10.5°	7.1°
60°	16.3°	13.3°	7.9°
90°	18°	14.8°	9.9°
120°	19.6°	16.9°	12.7°
180°	21.7°	18.4°	14.0°
Processing time	0.3 secs	0.6 secs	1.1 secs

3.4.4 Conclusiones y contribución

La principal conclusión, y a la vez la principal contribución, de este trabajo es comprobar que se puede obtener el DoA de un dispositivo IoT mediante la combinación de antenas de escaneo de haz en frecuencia, la técnica de salto en frecuencia y el algoritmo MUSIC, sin la necesidad de usar información compleja de la señal y con un FOV de 180°. Como se muestra en la Figura 15, el menor error angular se encuentra en ángulos cercanos a la perpendicular con respecto a la antena, es decir, en 0°.

Además, se ha comprobado que el error angular decrece cuando el número de canales que se emplean en el mecanismo de salto en frecuencia crece, por lo que se tiene un menor error cuando se emplean 11 canales en que cuando se emplean 3.

Por último, destacar que el sistema se ha comparado con el resto de publicaciones científicas que emplean un único AP para la determinación del DoA. En esta comparativa, que se muestra en Tabla 6, nuestro sistema destaca del resto en que no necesita del uso de información compleja de la señal para la obtención del ángulo, por lo que puede ser implementado con hardware comercial. Además, de entre los sistemas comparados que emplean solamente la RSSI, se tiene una mejor relación de FoV y error angular.

Tabla 6. Comparativa con otros sistemas DoA de la bibliografía

Sistema	Técnica de estimación de DOA	FoV	DoA error medio
ArrayTrack [22] Phaser [30] OpArray [51]	Array de antenas que emplea información de fase y tanto hardware como software previamente calibrado	180°	[51] 9°
CUPID [43] SpotFi [31]	Emplea CSI para estimar diferencias de fase empleando Antenas MIMO	180°	[43] 20° [31] 10°
VORBA [52]	Antenas <i>revolving</i> mecánicas	360°	[52] 22°
SBA [49], [50], [53]	<i>Switched Beam Antenna</i> controladas electrónicamente	360°	[50] 7.1°

Capítulo 3: Resumen de los artículos

Monopulso [1], [2]	Sistema monopulso RSSI empleando dos antenas de panel directivas	60°	[14] 4.3°
Este trabajo	FSA conectado a AP WiFi	180°	5.4°
FSA in BLE [54]	Array de dos FSA conectado a cuatro beacons BLE para estimar el DoD empleando RSSI	120°	3.7°

3.5 Evaluation of an indoor positioning system for added-value services in a mall

3.5.1 Breve introducción

En este segundo bloque de la tesis se trabaja en sistemas de localización activos, en los que no se necesita la intervención de los APs, sino que el dispositivo IoT, en nuestro caso un teléfono, es el encargado de recoger los datos que se emplean en los algoritmos de localización. En este primer trabajo de este bloque de artículos, publicado en uno de los congresos más importantes de localización en interiores, IPIN 2019 (*International Conference on Indoor Positioning and Indoor Navigation*), nos centramos en el diseño y evaluación de un *Indoor Positioning System* (IPS) generado mediante el algoritmo Freeloc.

Por consideraciones de diseño, se necesita que el IPS funcione sin el uso de los sensores inerciales. Se trata de restricciones de ahorro de batería, dado que se desea que interfiera lo mínimo posible en el funcionamiento normal del teléfono, funcione en segundo plano y no haga un uso intensivo de la batería. Además, también por consideraciones de diseño, no se necesita que tenga una precisión de centímetros, sino que se requiere de una precisión por zonas. Concretamente, el uso final del IPS es la localización de smartphones en centros comerciales con un nivel de precisión de zona a nivel tienda y/o pasillo. Es decir, cada una de las tiendas o pasillo donde se desea localizar a los visitantes, corresponde con una zona en el sistema.

Los grandes módulos en los que se divide el IPS son: i) Mapa digital; ii) Herramienta de calibración *offline*; y iii) Motor de localización. En nuestro caso, para la generación del mapa digital se modificó la herramienta Jinedit [55], desarrollada por el Spatio-Temporal Databases Laboratory from Pusan National University of South-Korea. Mediante esta aplicación, una vez generado el mapa digital del emplazamiento donde se desea establecer el sistema de localización, se tiene que realizar una calibración *offline* adquiriendo los *fingerprint* con las RSSI de los APs que se detectan en cada una de las zonas. Cada uno de los *fingerprint* es etiquetado con la zona en donde ha sido adquirido. Esta calibración se realiza mediante una aplicación Android que recibe los datos de las zonas del mapa digital generado. Una vez realizada la calibración, se emplea el heurístico Freeloc [56] para generar los vectores característicos de cada zona. Posteriormente, cuando se pone en marcha el sistema de localización y un teléfono a localizar entra en el edificio donde se tiene que localizar, el smartphone realiza un escaneo y obtiene un *fingerprint*. El conjunto de RSSI que forma el *fingerprint* es enviado al servidor de localización quien lo ordena según el procedimiento descrito en Freeloc y compara con los vectores generados. La zona estimada es aquella que tenga un vector de calibración con una mayor similitud al vector adquirido.

El sistema generado es evaluado de forma intensiva en un centro comercial de 25.000m² dividido en 69 zonas. Para la evaluación, se tiene en cuenta la heterogeneidad de los smartphones a localizar, la estabilidad del sistema en el tiempo y la influencia del fading provocado por las personas en la precisión del sistema. Por último, se evalúa la mezcla de calibraciones adquiridas por dos teléfonos diferentes

con el fin de comprobar si empleando este mecanismo de generación de vectores de calibración mediante dos *fingerprint* obtiene una mejor precisión.

3.5.2 Metodología

Los pasos que se han seguido para la realización de este trabajo son los siguientes:

- Generación de todos los módulos y herramientas que forman el IPS: i) Herramienta para la creación del mapa digital; ii) App de calibración; iii) Implementación de Freeloc; iv) App para generar rutas de validación; v) Procesamiento de resultados
- Calibración con cinco teléfonos diferentes y generación de motores de localización empleando Freeloc
- Realización de rutas de validación por el centro comercial empleando 9 teléfonos diferentes los días 1, 4, 11, 18, 34 y 74 posteriores a la calibración.
- Procesamiento y análisis de los resultados obtenidos.

3.5.3 Resultados

El primero de los resultados obtenidos está relacionado con las diferencias en la adquisición de RSSIs por cada uno de los diferentes teléfonos. Estas diferencias se observaron durante la realización de la calibración del centro comercial en la que se emplearon 5 teléfonos distintos. Se conoce de trabajos anteriores que incluso teléfonos con el mismo chipset WiFi obtienen diferentes valores de RSSI debido a la diferente orientación de las antenas, diferentes materiales de la carcasa, etc. Pero durante la calibración realizada en el centro comercial, las diferencias entre los AP detectados por cada uno de los smartphones fueron más elevadas de lo esperado. Estas diferencias se muestran en la Tabla 7. En ella se muestran los APs detectados durante el día de la calibración y, posteriormente, cada uno de los días que se llevaron a cabo las rutas de validación. Como se observa en la tabla, el día de la calibración, el smartphone etiquetado como #2 detectó 102 APs más que el smartphone #1. Otro dato que merece la pena destacar es que el número de APs detectado durante algunos días en los que se realizaron rutas de validación es mayor que el día de la realización de la calibración. Como por ejemplo el día 74 para el smartphone #1. Hay que tener en cuenta que durante la realización de las rutas de validación se cubre menos superficie del centro comercial que durante la realización de la calibración.

Tabla 7. Evolución de los APs a lo largo del tiempo

	Día calibración	Día 1	Día 4	Día 11	Día 18	Día 38	Día 74
Total of APs #1	758	761	755	757	727	767	779
Same APs #1	-	729	722	717	674	667	667
New APs #1	-	32	33	40	53	100	112
Total of APs #2	860	831	815	809	769	797	788
Same APs #2	-	780	766	764	720	747	696
New APs #2	-	51	49	45	49	50	92

Posteriormente se estudió la precisión en el tiempo de los motores de localización generados con cada uno de los cinco teléfonos con el fin de estudiar si la fase de calibración se puede realizar con cualquier teléfono o se requiere de algún teléfono con características especiales. En Figura 16 se muestra el error medio para cada una de los días en los que se realizaron rutas de validación. Para la obtención de los resultados se empleó la técnica de validación cruzada.

Figura 16. Evolución de Freeloc en el tiempo

El siguiente resultado destacable de este trabajo es conocer si el algoritmo empleado en la generación del IPS, Freeloc, se ve afectado por el fading provocado por las personas. Para comprobarlo, se realizaron varias rutas de validación a lo largo del centro comercial por la mañana, con una baja ocupación, y por la tarde, cuando la ocupación era mayor. En la Figura 17 se muestran los resultados de la validación cruzada, donde se puede observar como no se ve afectado dado que el percentil de los errores no varía con una baja o alta ocupación.

Figura 17. CDF con los errores de Freeloc en función de la ocupación

3.5.4 Conclusiones y contribución

A modo de conclusión, mediante la realización de este trabajo se ha implementado y validado el uso de Freeloc para la generación de un IPS de smartphones en un centro comercial con una precisión de zona. Para la generación del IPS se ha implementado todas las herramientas necesarias para su funcionamiento, incluyendo la herramienta para la creación del mapa digital, la App de calibración y la App para generar rutas de validación. Todas estas herramientas, junto con la

implementación de Freeloc realizada nos ha posibilitado la evaluación en un centro comercial con una clasificación zonal de 69 tiendas/pasillos.

Durante la fase de calibración se ha confirmado que, pese a que las diferencias entre los *fingerprint* adquiridos durante la calibración por los diferentes teléfonos son grandes, ya que cada teléfono detecta un número diferente de APs, la precisión y la estabilidad del IPS generado se mantiene a lo largo del tiempo. Y este resultado es similar independientemente del teléfono empleado. Por lo tanto, podemos afirmar que no es necesario ningún teléfono con características específicas para la generación del IPS. Por último, se ha demostrado también que Freeloc es estable frente al fading provocado por las personas dado que el error medio del sistema cuando no hay visitantes en el centro comercial es similar al error del sistema con gran afluencia.

3.6 An automatized contextual marketing system based on a wi-fi indoor positioning system

3.6.1 Breve introducción

Este trabajo [4], publicado en la revista MDPI Sensors, se trata del segundo trabajo del segundo bloque de la tesis y, por lo tanto, está relacionado con la localización de smartphones en centros comerciales. Se realizó con el fin de solventar las incógnitas que quedaron pendientes del trabajo anterior. En él intentamos resolver la cuestión de cuál sería el mejor algoritmo de posicionamiento para la implementación de un IPS en una gran infraestructura con necesidades de posicionamiento zonales. Además, se pone en contexto las posibilidades del uso de un IPS dentro de un Sistema de Marketing Contextual, donde el IPS es solamente una pieza más dentro de un complejo mecanismo que nos permite influir en las opciones de compra de los usuarios.

Tal y como se describe en el trabajo, para la generación de un Sistema de Marketing Contextual, junto con el IPS se necesita de los siguientes elementos: (i) un gestor de clientes, conocido como *Customer Relationship Management* (CRM); (ii) un gestor de contenidos, también conocido como *Content Manager system* (CMS); (iii) un panel de indicadores de rendimiento, habitualmente llamado *Key Performance Indicator* (KPI) panel; (iv) un sistema de comunicaciones con los clientes mediante email o notificaciones *push*; (vi) el mencionado IPS; y una (vii) aplicación móvil Android.

En este trabajo se ha comparado Freeloc frente a otros dos algoritmos ampliamente empleado en la localización en interiores como son KNN [17] y SVM [57]. La comparativa de los algoritmos se produjo en dos centros comerciales, teniendo que realizar todas las tareas necesarias para desplegar el IPS, desde la generación del mapa digital, la calibración de las zonas y la realización de las rutas de validación. Al igual que en el trabajo anterior, la comparativa se produjo en términos evolución de la precisión en el tiempo, funcionamiento ante la heterogeneidad del hardware y afección del fading.

Por último, todo el *dataset* obtenido ha sido puesto a disposición de la comunidad científica. Para ello se ha publicado en un repositorio público financiado bajo el proyecto europeo OpenAIRE. Se puede consultar y descargar en [58].

3.6.2 Metodología

Los pasos que se han seguido para la realización de este trabajo son los siguientes:

- Dado que este trabajo ya se parte del IPS implementado del trabajo anterior, se comenzó con la calibración y generación de rutas de validación del segundo centro comercial.

- Implementación de KNN y SVM para poder ser empleados como algoritmos de localización dentro del IPS.
- Generación de los motores de localización empleando las muestras de la calibración de los dos centros comerciales y los IPS con Freeloc, SVM y KNN.
- Procesamiento de las rutas de validación con los IPS generados.
- Obtención y representación de los resultados obtenidos.

3.6.3 Resultados

El primer resultado de este trabajo es la especificación completa del Sistema de Marketing Contextual, incluyendo todos los módulos que intervienen en su generación. A lo largo del trabajo se detalla cada uno de los módulos y sus relaciones entre ellos, explicando las principales funcionalidades y como intervienen en el proceso de compra de los visitantes de un centro comercial. En la Figura 18 se representa las relaciones entre los módulos que forman el Sistema de Marketing Contextual.

Figura 18. Representación del Sistema de Marketing Contextual

Una vez que hemos definido el Sistema de Marketing Contextual, y como el IPS es uno de los módulos fundamentales del mismo, se obtuvieron los resultados de la precisión de los diferentes algoritmos de localización. El resultado de evaluar todas las rutas de validación mediante el mecanismo de validación cruzada para los dos centros comerciales empleando Freeloc se muestra en la Figura 19 Izq, KNN se muestra en Figura 19 centro y SVM en la Figura 19 Dcha. Se puede observar como para SVM y KNN el error medio aumenta a lo largo del tiempo y se tiene un valor de error más elevado que para el caso de Freeloc. Además, el error medio de los motores generados con cinco teléfonos distintos es menor para Freeloc que para el resto de algoritmos. Por lo tanto, estamos en condiciones de afirmar que Freeloc presenta un menor error medio, es más estable a la evolución del tiempo y puede ser empleado con una

calibración realizada independientemente del smartphone empleado. Sin embargo, estas afirmaciones no son válidas para SVM ni para KNN.

Figura 19. Precisión de Freiloc (izq), KNN (centro) y SVM (dcha)

Por último, se estudió la afectación del fading causado por las personas en los dos centros comerciales. En la Figura 20 se muestra el CDF donde se indica el percentil de muestras que están por debajo de un determinado error, donde en las figuras de la izquierda se muestran los valores para el centro comercial 1 y en los de la derecha para el centro comercial 2, empleado en las figuras de la parte superior Freiloc, en las figuras del centro SVM y KNN en la parte inferior. Se puede observar como el IPS generado con Freiloc tiene el mayor porcentaje de muestras correctamente situadas en la zona recogida, estas son las muestras con error 0, alrededor del 60% y un 90% de las muestras con un error por debajo de 30 metros para los cinco teléfonos.

Figura 20. CDF (izq) para centro comercial 1 y (dcha) para centro comercial 2 empenado Freeloc (superior), SVM (centro) y KNN (inferior)

3.6.4 Conclusiones y contribución

A modo de conclusiones, podemos confirmar que se ha definido con detalle un Sistema de Marketing Contextual, prestando atención a todos los módulos que forman el mismo y las relaciones entre ellos. Dentro de los módulos, uno de los más relevantes es el IPS, dado que nos permite conocer la posición de los visitantes de una gran infraestructura. Por ello, se han definido la metodología y se han generado las herramientas para crear un IPS bajo el punto de vista de una empresa de servicios TICs. Para ello, todos los procesos y herramientas que forman el IPS tienen que se escalables, pudiendo aumentar el número de infraestructuras monitorizadas sin tener que aumentar el personal que las gestionan.

Otras de las contribuciones importantes de este trabajo es encontrar el algoritmo de localización de smartphones en interiores que, empleando la señal proveniente de los APs WiFi y sin hacer uso de los sensores inerciales del teléfono, tenga una mejor precisión a nivel zonal en términos de estabilidad en el tiempo, heterogeneidad de dispositivos y afección por el fading provocado por las personas. Para ello, se realizó una evaluación exhaustiva en dos centros comerciales a lo largo del tiempo y empleando hasta diez teléfonos de tres algoritmos que han sido empleados en trabajos anteriores para la generación de IPS como son: Freeloc, KNN y SVM. De los resultados obtenidos y explicados en el párrafo anterior, se observa que Freeloc es el algoritmo que presenta un mejor rendimiento antes todos los parámetros evaluados y que es factible la implementación de un IPS en una gran infraestructura empleando este algoritmo.

Capítulo 4

Conclusiones y líneas futuras

4.1 Conclusiones

Los sistemas de localización en interiores de dispositivos IoT son una realidad, cuya implantación ha sido realizada con éxito en todo tipo de ámbitos de aplicación, tanto industriales, comerciales, como educativos. Pero no existe un estándar predominante, sino que en función de las necesidades del sistema a generar se emplea la tecnología más apropiada. De entre todas las tecnologías que se pueden emplear para la generación de este tipo de sistemas, destacan los basados en el empleo de la señal proveniente de redes WiFi. Esto es debido a que en la mayoría de instalaciones donde se desea establecer un sistema de localización *indoor* ya existen redes WiFi desplegadas con el fin de dotar de conectividad a los visitantes. Dentro del paradigma de sistemas de localización indoor, en esta tesis nos hemos centrado en los sistemas de localización pasivos basados en DoA y, por otro lado, se ha trabajado en los sistemas de localización activos de smartphones en centros comerciales. La tesis se ha dividido en dos grandes bloques, uno para cada tipo de los sistemas estudiados.

Con respecto del primer bloque de la tesis, a modo de conclusión, se ha demostrado que mediante los *sniffer* híbridos analógicos-digitales generados empleando hardware comercial se puede determinar el DoA de dispositivos IoT sin necesidad de emplear información compleja de la señal. Se trata de sistemas que solamente emplean RSSI, por lo que requiere de un procesamiento de señal asequible para cualquier hardware comercial. Los sistemas generados tienen un FoV de 60°, dado que es el rango en el que se tiene una función monopolso unívoca. Estos sistemas han sido testeados en entornos reales y han mostrado un bajo error angular, permitiendo el posicionamiento en (x,y) mediante la combinación de dos dispositivos HAD.

Continuando con el sistema generado en el trabajo anterior, se ha comprobado que, debido a que los diagramas de radiación son cambiantes en función de la distancia, en entornos de near-field la pendiente de la función monopolso varía. Estas variaciones provocan que se tenga que emplear la función monopolso correspondiente a la distancia o el error angular crece. Por lo tanto, se tiene que conocer de antemano la distancia al dispositivo a localizar con el fin de emplear la función monopolso correspondiente.

Otra conclusión de este primer bloque es que mediante la combinación de la función monopolso y el estándar 802.11mc se puede generar un sistema radar 2D que permite la localización de dispositivos IoT empleando un único AP. Este protocolo emplea el mecanismo RTT para calcular la distancia desde el dispositivo hasta el AP. Para poder implementar este sistema, junto con la función monopolso, se tuvo que generar un nuevo *sniffer* empleando un AP compatible con RTT como es el Yocto Wild. El software de este equipo fue modificado para poder recibir de forma simultánea la RSSI recibida por las dos antenas directivas y la RTT. Gracias a tener estos parámetros de forma simultánea, se puede calcular el DoA y la distancia al dispositivo, lo que permite generar un sistema de posicionamiento 2D empleando un único AP.

Como última conclusión dentro de este bloque, podemos afirmar que hemos demostrado la posibilidad de crear un sistema DoA empleando un AP con un FoV de 180°. Para la generación del sistema se ha empleado antenas con haz de escaneo en

frecuencia (*frequency-beam scanning antenna – SFA*), *channel-hopping* y el algoritmo MUSIC. Se ha demostrado que el error angular disminuye a medida que se amplían el número de canales empleados, por lo que el menor error se encuentra cuando el número de canales empleado es $N=11$. Además, también se ha comprobado que el menor error angular se obtiene cuando el dispositivo a localizar se sitúa perpendicular a la antena. Con estas dos condiciones se tiene un RMSE de 7.1° .

Por último, con respecto a las conclusiones del segundo bloque de artículos, se ha implementado y demostrado la viabilidad de la implementación de un Sistema de Marketing Contextual empleando un sistema de posicionamiento (*Indoor Positioning System - IPS*). El sistema ha sido testeado exhaustivamente en dos centros comerciales, comparando varios algoritmos para la generación del IPS: SVM, KNN y Freeloc. Del conjunto de pruebas realizadas, Freeloc presentó una mayor precisión en cuanto a las interrogantes de estabilidad en el tiempo, heterogeneidad del hardware y variación frente al *fading* provocado por las personas.

4.2 Líneas futuras

Tras las contribuciones presentadas en este trabajo de tesis, se abren varios frentes de investigación que pueden continuar contribuyendo a los sistemas de localización basados en la función monopolso, así como a los sistemas de localización basados en RSSI para grandes infraestructuras.

Las principales líneas futuras con respecto a los sistemas de localización empleando la función monopolso, pensamos que las principales contribuciones futuras pueden ser:

- Mediante el uso de dos o más *sniffer* HAD que combinen de forma simultánea el AoA y el ranging, se puede generar algoritmos de localización que tengan una mayor precisión, así como ampliar el rango de posibles aplicaciones.
- El uso de antenas del tipo haz de escaneo en frecuencia junto con la combinación de RTT puede producir sistemas de localización de dispositivos IoT empleando un único punto de acceso con un FoV de 180°
- A medida que aumente el número de dispositivos que ofrecen la métrica RTT en instalaciones reales como pueden ser universidades, aeropuertos, centros comerciales, etc., se podría realizar la implementación del sistema en un entorno real empleando los APs desplegados.

Con respecto a los sistemas de localización basados en RSSI en grandes instalaciones como los propuestos en este trabajo de tesis, las líneas futuras de esta investigación serían las siguiente:

- Evaluación de este tipo de sistemas a lo largo de varios meses con el fin de conocer la duración de los motores de localización. Durante este trabajo

se han evaluado los IPS a lo largo de varias semanas, pero se desconoce el tiempo exacto durante el que se podrían seguir utilizando.

- Dado que la fase de calibración es una de las más tediosas de la implantación de este tipo de sistema, mediante mecanismos de autocalibración y autogeneración de los motores de localización, se podría extender el tiempo de funcionamiento del sistema sin tener que realizar nuevas calibraciones.

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Capítulo 5

Factor de impacto de las publicaciones

GLOSARIO

J. L. Gomez-Tornero, D. Canete-Rebenaque, J. A. Lopez-Pastor, and A. S. Martinez-Sala, "Hybrid Analog-Digital Processing System for Amplitude-Monopulse RSSI-Based MIMO WiFi Direction-of-Arrival Estimation," *IEEE J. Sel. Top. Signal Process.*, vol. 12, no. 3, pp. 529–540, 2018.

Factor de impacto en el momento de la publicación: 6.688

Cuartil: Q1 in Engineering, Electrical and Electronic

Citas: 21

J. A. Lopez-Pastor, A. Gomez-Alcaraz, D. Canete-Rebenaque, A. S. Martinez-Sala, and J. L. Gomez-Tornero, "Near-Field Monopulse DoA Estimation for Angle-Sensitive Proximity WiFi Readers," *IEEE Access*, vol. 7, pp. 88450–88460, 2019.

Factor de impacto en el momento de la publicación: 3.745

Cuartil: Q1 in Engineering, Electrical and Electronic

Citas: 12

J. A. Lopez-Pastor, P. Arques-Lara, J. J. Franco-Penaranda, A. J. Garcia-Sanchez, and J. L. Gomez-Tornero, "Wi-Fi RTT-Based Active Monopulse RADAR for Single Access Point Localization," *IEEE Access*, vol. 9, pp. 34755–34766, 2021.

Factor de impacto en el momento de la publicación: 3.367

Cuartil: Q2 in Engineering, Electrical and Electronic

Citas: 0

J. A. López-Pastor, A. J. Ruiz-Ruiz, A. J. García-Sánchez, and J. L. Gómez-Tornero, "An automatized contextual marketing system based on a wi-fi indoor positioning system," *Sensors*, vol. 21, no. 10, pp. 1–26, 2021.

Factor de impacto en el momento de la publicación: 3.576

Cuartil: Q2 in Engineering, Electrical and Electronic

Citas: 0

(Fuente: JCR Science Edition y Google Scholar)

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