Collaborative Techniques for Indoor Positioning Systems

Doctoral Thesis

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ABSTRACT

The demand for Indoor Positioning Systems (IPSs) developed specifically for mobile and wearable devices is continuously growing as a consequence of the expansion of the global market of Location-based Services (LBS), increasing adoption of mobile LBS applications, and ubiquity of mobile/wearable devices in our daily life. Nevertheless, the design of mobile/wearable devices-based IPSs requires to fulfill additional design requirements, namely low power consumption, reuse of devices' built-in technologies, and inexpensive and straightforward implementation. Within the available indoor positioning technologies, embedded in mobile/wearable devices, IEEE 802.11 Wireless LAN (Wi-Fi) and Bluetooth Low Energy (BLE) in combination with lateration and fingerprinting have received extensive attention from research communities to meet the requirements. Although these technologies are straightforward to implement in positioning approaches based on Received Signal Strength Indicator (RSSI), the positioning accuracy decreases mainly due to propagation signal fluctuations in Line-of-sight (LOS) and Non-line-of-sight (NLOS), and the heterogeneity of the devices' hardware. Therefore, providing a solution to achieve the target accuracy within the given constraints remains an open issue.

The motivation behind this doctoral thesis is to address the limitations of traditional IPSs for human positioning based on RSSI, which suffer from low accuracy due to signal fluctuations and hardware heterogeneity, and deployment cost constraints, considering the advantages provided by the ubiquity of mobile devices and collaborative and machine learning-based techniques. Therefore, the research undertaken in this doctoral thesis focuses on developing and evaluating mobile device-based collaborative indoor techniques, using Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs), for human positioning to enhance the position accuracy of traditional indoor positioning systems based on RSSI (i.e., lateration and fingerprinting) in real-world conditions.

The methodology followed during the research consists of four phases. In the

first phase, a comprehensive systematic review of Collaborative Indoor Positioning Systems (CIPSs) was conducted to identify the key design aspects and evaluations used in/for CIPSs and the main concerns, limitations, and gaps reported in the literature. In the second phase, extensive experimental data collections using mobile devices and considering collaborative scenarios were performed. The data collected was used to create a mobile device-based BLE database for testing ranging collaborative indoor positioning approaches, and BLE and Wi-Fi radio maps to estimate devices' position in the non-collaborative phase. Moreover, a detailed description of the methodology used for collecting and processing data and creating the database, as well as its structure, was provided to guarantee the reproducibility, use, and expansion of the database. In the third phase, the traditional methods to estimate distance (i.e., based on Logarithmic Distance Path Loss (LDPL) and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-Nearest Neighbors (k-NN)) were described and evaluated in order to present their limitations and challenges. Also, two novel approaches to improve distance and positioning accuracy were proposed. In the last phase, our two proposed variants of collaborative indoor positioning system using MLP ANNs were developed to enhance the accuracy of the traditional indoor positioning approaches (BLE–RSSI lateration-based and fingerprinting) and evaluated them under real-world conditions to demonstrate their feasibility and benefits, and to present their limitations and future research avenues.

The findings obtained in each of the aforementioned research phases correspond to the main contributions of this doctoral thesis. Specifically, the results of evaluating our CIPSs demonstrated that the first proposed variant of mobile device-based CIPS outperforms the positioning accuracy of the traditional lateration-based IPSs. Considering the distances among collaborating devices, our CIPS significantly outperforms the lateration baseline in short distances ($\leq 4\,\mathrm{m}$), medium distances ($>4\,\mathrm{m}$ and $\leq 8\,\mathrm{m}$), and large distances ($> 8\,\mathrm{m}$) with a maximum error reduction of 49.15 %, 19.24 %, and 21.48 % for the "median" metric, respectively. Regarding the second variant, the results demonstrated that for short distances between collaborating devices, our collaborative approach outperforms the traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting with a maximum error reduction of 23.41% and 19.49% for the "75th percentile" and "90th percentile" metric, respectively. For medium distances, our proposed approach outperforms the traditional IPSs based on BLE–fingerprinting in the first 60% and after the 90% of cases in the

Empirical Cumulative Distribution Function (ECDF) and only partially (20% of cases in the ECDF) the traditional IPSs based on Wi-Fi–fingerprinting. For larger distances, the performance of our proposed approach is worse than the traditional IPSs based on fingerprinting.

Overall, the results demonstrate the usefulness and usability of our CIPSs to improve the positioning accuracy of traditional IPSs, namely IPSs based on BLE–lateration, BLE–fingerprinting, and Wi-Fi–fingerprinting under specific conditions. Mainly, conditions where the collaborative devices have short and medium distances between them. Moreover, the integration of MLP ANNs model in CIPSs allows us to use our approach under different scenarios and technologies, showing its level of generalizability, usefulness, and feasibility.

RESUMEN

La demanda de Sistemas de Posicionamiento Indoor (IPSs por sus siglas en inglés) desarrollados específicamente para dispositivos móviles y wearables está en constante crecimiento como consecuencia de la expansión del mercado global de Servicios Basados en Localización (LBS por sus siglas en inglés), el aumento en la adopción de aplicaciones móviles de LBS y la ubicuidad de los dispositivos móviles/wearables en nuestra vida diaria. Sin embargo, el diseño de IPSs basados en dispositivos móviles/wearables requiere cumplir con requisitos adicionales de diseño, como un bajo consumo de energía, reutilización de tecnologías incorporadas en los dispositivos y una implementación sencilla y económica. Dentro de las tecnologías de posicionamiento indoor disponibles en dispositivos móviles/wearables, IEEE 802.11 Wireless LAN (Wi-Fi) y Bluetooth Low Energy (BLE), combinados con lateration y fingerprinting, han recibido una gran atención por parte de las comunidades de investigación para satisfacer los requisitos mencionados anteriormente. Sin embargo, aunque estas tecnologías son sencillas de implementar en los enfoques de posicionamiento basados en el Indicador de Intensidad de Señal Recibida (RSSI por sus siglas en inglés), la precisión de posicionamiento disminuye principalmente debido a las fluctuaciones de la señal de propagación en Línea de vista (LOS por sus siglas en inglés) y Fuera de línea de vista (NLOS por sus siglas en inglés), y la heterogeneidad del hardware de los dispositivos. Por lo tanto, proporcionar una solución para lograr la precisión de posicionamiento deseada dentro de las limitaciones dadas sigue siendo un problema abierto.

La motivación detrás de esta tesis doctoral es abordar las limitaciones de los IPSs tradicionales para el posicionamiento humano basado en RSSI, los cuales sufren de baja precisión debido a las fluctuaciones de señal y la heterogeneidad del hardware, y de limitaciones de costo de implementación, considerando las ventajas proporcionadas por la ubicuidad de los dispositivos móviles y las técnicas colaborativas y basadas en el aprendizaje automático. Por lo tanto, la investigación llevada a cabo

en esta tesis doctoral se centra en el desarrollo y evaluación de técnicas colaborativas basadas en dispositivos móviles y utilizando utilizando Redes Neuronales Artificiales (MLP por sus siglas en inglés) de Perceptrón Multicapa (MLP)MLP (ANNs por sus siglas en inglés) para el posicionamiento humano, con el fin de mejorar la precisión de posición de los sistemas tradicionales de posicionamiento indoor basados en RSSI (es decir, lateration y fingerprinting) en condiciones del mundo real.

La metodología seguida durante la investigación consta de cuatro fases. En la primera fase, se realizó una revisión sistemática exhaustiva de los Sistemas de Posicionamiento Indoor Colaborativos (CIPSs por sus siglas en inglés) para identificar los aspectos clave de diseño y evaluaciones utilizados en/para CIPSs, así como las principales preocupaciones, limitaciones y brechas reportadas en la literatura. En la segunda fase, se realizaron extensas recolecciones de datos experimentales utilizando dispositivos móviles y considerando escenarios colaborativos. Los datos recopilados se utilizaron para crear una base de datos basada en BLE para probar enfoques de posicionamiento indoor colaborativos, y mapas de radio BLE y Wi-Fi para estimar la posición de los dispositivos en la fase no colaborativa. Además, se proporcionó una descripción detallada de la metodología utilizada para la recolección y procesamiento de datos y la creación de la base de datos, así como su estructura, para garantizar la reproducibilidad, uso y expansión de la base de datos. En la tercera fase, se describieron y evaluaron los métodos tradicionales para estimar la distancia (es decir, basados en (es decir, basados en Pérdida de Trayectora de Distancia Logarítmica (LDPL por sus siglas en inglés) y lógica difusa) y la posición (es decir, RSSI-lateration y fingerprinting–*k*-NN para presentar sus limitaciones y desafíos. Además, se propusieron dos nuevos enfoques para mejorar la precisión de distancia y posicionamiento. En la última fase, se desarrollaron nuestras dos variantes propuestas de sistemas de posicionamiento indoor colaborativos utilizando MLP ANNs para mejorar la precisión de los enfoques tradicionales de posicionamiento indoor (BLE-RSSI basados en lateration y fingerprinting) y se evaluaron en condiciones del mundo real para demostrar su factibilidad y beneficios, así como para presentar sus limitaciones y futuras líneas de investigación.

Los hallazgos obtenidos en cada una de las fases de investigación mencionadas corresponden a las principales contribuciones de esta tesis doctoral. Específicamente, los resultados de la evaluación de nuestros CIPSs demostraron que la primera variante propuesta de CIPS basado en dispositivos móviles supera la precisión de posicionamiento de los IPSs basados en lateration tradicionales. Considerando las distancias entre dispositivos colaborativos, nuestro CIPS supera significativamente el sistema de referencia basado en lateration en distancias cortas ($\leq 4\,\mathrm{m}$), distancias medias ($>4\,\mathrm{m}$ y $\leq 8\,\mathrm{m}$), y distancias largas ($> 8\,\mathrm{m}$), con una reducción máxima del error del 49,15%, 19,24%, y 21,48% para la métrica de "mediana", respectivamente. En cuanto a la segunda variante, los resultados demostraron que para distancias cortas entre dispositivos colaborativos, nuestro enfoque colaborativo supera a los IPSs tradicionales basados en BLE-fingerprinting y Wi-Fi-fingerprinting con una reducción máxima del error del 23,41% y 19,49% para la métrica del "75 percentil" y "90 percentil ", respectivamente; para distancias medias, nuestro enfoque propuesto supera a los IPSs tradicionales basados en BLE-fingerprinting en el primer 60% y después del 90% de los casos en la Función de Distribución Acumulativa Empírica (ECDF por sus siglas en inglés) y solo parcialmente (20% de los casos en el ECDF) los IPSs tradicionales basados en Wi-Fi-fingerprinting; para distancias más grandes, el rendimiento de nuestro enfoque propuesto es peor que el de los IPSs tradicionales basados en fingerprinting.

En general, los resultados demuestran la utilidad y usabilidad de nuestros CIPSs para mejorar la precisión de posicionamiento de los IPSs tradicionales, es decir, los IPSs basados en BLE–lateration, BLE–fingerprinting y Wi-Fi–fingerprinting bajo condiciones específicas. Principalmente, en condiciones en las que los dispositivos colaborativos tienen distancias cortas y medias entre ellos. Además, la integración del modelo de MLP ANNs en nuestros CIPSs nos permite utilizar nuestro enfoque con diferentes escenarios y tecnologías, mostrando su nivel de generalización, utilidad y viabilidad.

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LIST OF ACRONYMS

AI	Artificial Intelligence
ANN	Artificial Neural Network
AoA	Angle of Arrival
AP	Access Point
BLE	Bluetooth Low Energy
B-MLE	Biased-maximum Likelihood Estimator
CDF	Cumulative Distribution Function
CIPS	Collaborative Indoor Positioning System
CRLB	Cramér Rao Lower Bound
CTP	Collection Tree Protocol
D2D	Device to Device
DNN	Deep Neural Network
DR	Dead Reckoning
DSA	Distributed Stochastic Approximation
ECDF	Empirical Cumulative Distribution Function
EKF	Extended Kalman Filter
GDOP	Geometric Dilution of Precision
GNSS	Global Navigation Satellite System
GT	Ground-Truth
IMU	Inertial Measurement Unit
IPS	Indoor Positioning System
KF	Kalman Filter

k-NN	k-Nearest Neighbors
LBS	Location-based Services
LDPL	Logarithmic Distance Path Loss
LOS	Line-of-sight
LS	Least Square
LTE	Long-Term Evolution
MAC	Media Access Control
MAD	Median Absolute Deviation
MLP	Multilayer Perceptron
MSE	Mean Square Error
NLLS	Non-Linear Least Square
NLOS	Non-line-of-sight
PDR	Pedestrian Dead Reckoning
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF	Radio Frequency
RFID	Radio-Frequency Identification
RLOWESS	Robust Locally Weighted Scatterplot Smoothing
RMSE	Root Mean Square Error
RSS	Received Signal Strength
RSSI	Received Signal Strength Indicator
SISO	Single Input Single Output
SOTA	state-of-the-art
SSE	Sum Square Error
TDoA	Time Difference of Arrival
ToA	Time of Arrival
ToA/ToF	Time of Arrival/Flight
TWR	Two-way Ranging
UDP	User Datagram Protocol

UI	User Interface
UAV	Unmanned Aerial Vehicle
UTDoA	Uplink Time-Difference-of-Arrival
UUID	Universally Unique IDentifier
UWB	Ultra-wide band
VLC	Visible Light Communication
WASP	Wireless Application Service Provider
Wi-Fi	IEEE 802.11 Wireless LAN
WSN	Wireless Sensor Network

1 INTRODUCTION

1.1 Introduction and motivation

The global market of Location-based Services (LBS) is growing rapidly due to the ubiquity of mobile and wearable devices in our daily life [1, 2]. This has increased the demand for Indoor Positioning Systems (IPSs), especially those for mobile and wearable devices. In addition to the common IPSs design requirements (e.g., high position estimation accuracy and, if possible, the reuse of infrastructure deployed in the environments) [3], mobile and wearable device-based positioning systems should consider low power consumption, reuse of devices' built-in technologies, inexpensive and straightforward implementation as main requirements [4]. Meeting all these requirements remains an open challenge for the scientific community. Consequently, the scientific community focuses on improving positioning technologies, techniques, and methods to provide solutions with the best trade-off between the aforementioned requirements, primarily focusing on position estimation accuracy.

Within the available positioning technologies for IPS, IEEE 802.11 Wireless LAN (Wi-Fi) and Bluetooth Low Energy (BLE) are widely used due to their already embedded nature in mobile, wearable, and IoT devices [3, 5] and the last one also due to their low energy profile and inespensiveness [6]. Despite the straightforward implementation of these technologies in positioning systems based on Received Signal Strength Indicator (RSSI), the heterogeneity of the devices' hardware and the fluctuations in the signal propagation caused by the environment affect the signal's propagation, especially in Non-line-of-sight (NLOS) conditions, leading to a decrease in positioning accuracy. The most popular approaches to mitigate these fluctuations are fingerprinting, lateration, and mathematical modeling of signal propagation. However, these approaches have some drawbacks, such as the difficulty of modeling signal propagation in various environments and conditions; expensive and complex maintenance and update of RSSI-signatures databases; insufficient number and poor deployment (placement) of reference beacons in the environment.

As it can be noticed, the most popular approaches in the literature impose restrictions and present additional challenges from the point of view of development, implementation, and use. To address these challenges, the scientific community has been investigating a variant of traditional IPSs based on the collaboration between devices, which takes advantage of the increasing density of mobile and wearable devices in indoor environments, their ubiquity, and the duality of wireless technologies (i.e., communication and positioning use).

Collaborative Indoor Positioning Systems (CIPSs) aim to provide better performance of positioning systems by exploiting the advantages of traditional positioning approaches (e.g., based on fingerprinting or lateration) and mitigating their drawbacks through the collaboration of neighboring devices using wireless communications. CIPSs augment the coverage area of traditional IPSs by broadcasting positioning data between users [7, 8, 9]; decrease the positioning infrastructure cost and complexity while improving users' positioning accuracy [10, 11, 12]; decrease positioning uncertainty due to poor geometric location of anchors [13, 14], and decrease positioning in harsh and NLOS environments by using the surrounding users as auxiliary anchor nodes [15, 16, 17].

In detail, in the research field of IPSs, based on the role played by diverse actors/users in the system, we can identify two primary types of IPSs, the non-collaborative and collaborative [15, 18, 17, 19]. Both terms are related to the operational phase, where the position is estimated, and not to the data collection phase. Non-collaborative systems do not take into account the involvement of other actors/users in their positioning algorithms. Contrarily, collaborative systems determine the position due to the indirect/direct interoperability between nearby actors/users or several IPSs. It should be noted that sensor/data fusion and collaborative approaches are not the same. While the first one focuses on fusing sensors' data from a single user to estimate position, the second one aims to estimate position using independent actors/users, which exchange information and the relative distance computed between them.

In the literature, there is a vast number of proposed collaborative positioning systems designed for different users (e.g., sensors, robots, aerial and ground vehicles), scenarios (i.e., outdoor and indoor), and applications (e.g., autonomous vehicles/-drones positioning in warehouses and factories). However, the number of proposed

CIPSs that involve human users is moderate [3]. Each CIPS solution requires taking into account in its design the requirements, challenges, and resources available for the specific application. For example, the precision, accuracy, and latency required for positioning autonomous vehicles/drones in whare houses are not the same as for positioning people in a mall. Furthermore, contrary to the CIPSs for vehicles/-drones, those for humans are usually restricted to using devices (already) in use by the user (i.e., wearable/mobile devices), which inherently imposes battery and computational power constraints.

The motivation behind this doctoral thesis is to address the limitations of traditional IPSs for human positioning based on RSSI, which suffer from low accuracy due to signal fluctuations and hardware heterogeneity, and deployment cost constraints, considering the advantages provided by the ubiquity of mobile devices and collaborative and machine learning-based techniques. Specifically, the ubiquity of mobile devices has created an unprecedented opportunity to improve the low positioning accuracy of traditional IPS approaches based on RSSI without increasing the deployment cost. Also, in recent years, machine learning-based IPS techniques have shown significant promise in improving accuracy. However, most of these techniques focus on individual device-based approaches, which limits the potential of the solutions. Moreover, collaborative techniques together with machine learning-based techniques can significantly improve the accuracy of IPSs focus on human positioning and heterogeneous devices. So, in this thesis, we focus our research on the development and evaluation of mobile device-based collaborative indoor techniques, using Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs), for human positioning to enhance the position accuracy of traditional IPSs based on RSSI. It should be noted that throughout this thesis, we use the convention RSSI instead of Received Signal Strength (RSS) because we use mobile devices based on the android library to obtain the measurements and in its specifications [20] indicates that the measurements obtained are in RSSI.

1.2 Research objectives and questions

The principal objective of this thesis is to develop and evaluate mobile device-based collaborative indoor techniques for human positioning to enhance the position accuracy of traditional indoor positioning systems based on RSSI. In detail, the objectives are summarized as follows:

First objective: To gain an overview of the state-of-the-art in the field, and map the principal technologies, techniques, and methods used for collaborative indoor positioning approaches, as well as the main architectures and infrastructures used.

Second objective: To create an open access BLE database for the research community, using mobile devices which simultaneously act as transmitters and receivers, for experimentation and evaluation of non-collaborative and collaborative indoor positioning under diverse conditions.

Third objective: To describe and experimentally analyze non-collaborative methods to estimate distance (i.e., based on Logarithmic Distance Path Loss (LDPL) model and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-Nearest Neighbors (k-NN)). Additionally, to describe and analyze the behavior of BLE signals propagation in indoor environments, considering mobile devices as transmitters and receivers.

Fourth objective: To develop and evaluate mobile device-based collaborative techniques to enhance the position accuracy of traditional IPSs based on lateration and fingerprinting–k-NN methods, and study and demonstrate the usefulness of the collaborative approach under various conditions.

The aforementioned objectives have been stated to address the following research questions:

RQ1: What are the infrastructures, architectures, technologies, techniques, methods, and evaluation aspects used in/for CIPSs, and what are the current trends and the main gaps in CIPS?

RQ2: How can the ranging-based collaborative indoor positioning systems be experimentally tested and validated considering heterogeneous mobile devices?

RQ3: What are the limitations and challenges of the traditional methods to estimate distance (i.e., based onLDPL model and fuzzy logic) and position (lateration and fingerprinting–k-NN) based on BLE/Wi-Fi-RSSI and how can the positioning accuracy and robustness of LDPL model and lateration be improved?

RQ4: How can the positioning accuracy of traditional IPSs based on RSSI measurements (i.e., lateration and fingerprinting) be enhanced by the collaboration of surrounding devices/users?

The research questions are addressed in the chapters and publications indicated in Table 1.1.

Table 1.1 Research question – chapters – publications.

Research question	Thesis chapter	Publications
Research question 1	Chapter 2 & Chapter 6	[3]
Research question 2	Chapter 3 & Chapter 6	[21]
Research question 3	Chapter 4 & Chapter 6	[21, 4, 6]
Research question 4	Chapter 5 & Chapter 6	[22]

1.3 Research methodology

To achieve the aforementioned objectives, we conducted research between 2019 and 2022, which was divided into four sequential phases.

First phase: A comprehensive systematic review of CIPSs was conducted to identify the design aspects (i.e., infrastructure, architecture, technology, technique, and method) and the evaluations used in/for the identified CIPSs. Furthermore, the main concerns, limitations, and gaps in the research field were reported.

Second phase: Data collection campaigns were performed in an office and a lobby scenario based at University Jaume I (Castellón, Spain) and Tampere University (Tampere, Finland), respectively, based on mobile devices considering the devices' collaboration (simultaneous transmission/reception between them). The data collected was used to create mobile device-based BLE databases for testing non-collaborative and collaborative indoor positioning approaches. Also, BLE and Wi-Fi radio maps were created to estimate devices' position in the non-collaborative phase based on fingerprinting and lateration. Additionally, a detailed description of the methodology used for the collection and processing of data and creation of the databases, as well as their structures, were provided to guarantee the reproducibility, use, and expansion of the databases.

Third phase: The traditional non-collaborative methods to estimate distance (i.e., based on LDPL model and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-NN) were described and evaluated to present their limitations and challenges and to use them as a performance benchmark for our CIPS. The behavior of BLE signals propagation in indoor environments, considering mobile devices as transmitters and receivers, was described and analyzed. Also, two novel approaches to improve distance and positioning accuracy were proposed and evaluated.

Fourth phase: Our proposed collaborative indoor positioning system using Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs) was developed to enhance the accuracy of the traditional indoor positioning methods (RSSI-lateration and fingerprinting–k-NN) and evaluated it under real-world conditions to demonstrate its feasibility and benefits. Moreover, its limitations and future research avenues were presented.

The findings obtained in each of the aforementioned research phases correspond one-on-one to the main objectives stated in this doctoral thesis.

1.4 Contributions

In detail, the contributions of this thesis are summarized as follows:

Research contribution:

Overview of state-of-the-art in collaborative indoor positioning systems: The Author presents to the readers an overall view of the infrastructure, architectures, technologies, techniques, and methods used in/for CIPSs, and how they are used together to estimate the user/device's position. Also, the Author provides a view of trends, open issues, gaps, limitations, and future works of CIPSs reported in the literature.

Databases and testing scenarios: The Author provides mobile device-based BLE databases for testing non-collaborative and collaborative indoor positioning approaches, considering bidirectional and simultaneous transmission/reception between devices. The databases contain experimental data collected in two different real indoor scenarios, an office and a lobby scenario, based at University Jaume I (Castellón, Spain) and Tampere University (Tampere, Finland), respectively. In each scenario, various mobile device arrangements were configured, and real NLOS conditions (i.e., employees doing office duties, people intentionally walking and/or sitting in their work areas, and normal lobby conditions). Also, a calibration mobile devices arrangement in Line-of-sight (LOS) conditions was designed. A detailed description of the methodology used for the data collection process, data post-processing, and the database structure is provided to ensure its reproducibility and reuse in other scenarios. In addition, the Author provides BLE and Wi-Fi radio maps created to perform fingerprinting and lateration approaches in the aforementioned scenarios. The radio maps contain the information of the BLE anchors deployed in the office scenario and the Wi-Fi Access Points (APs) available in the lobby scenario.

Analysis of non-collaborative RSSI-based methods and BLE signals: The Author provides an analysis of the behavior of the BLE signals, transmitted and received by mobile devices, in indoor environments. The limitations and challenges of the diverse methods based on RSSI to estimate distance (i.e., based on LDPL model and fuzzy logic) and position (i.e., RSSI–lateration and fingerprinting–k-NN) in NLOS conditions are stated. Moreover, the Author proposed two novel solutions to improve distance and positioning accuracy. The first is based on a fuzzy logic classifier that mitigates the effect of BLE signals fluctuations indoors and outperforms approaches based on LDPL. The second is a novel lateration BLE-RSSI method based on combinatorial anchors selection to enhance the accuracy and reliability of the position estimated.

Collaborative indoor positioning system: The Author provides a collaborative indoor positioning system using MLP ANNs to improve the accuracy of the traditional indoor positioning methods, namely RSSI-lateration and fingerprinting–k-NN, under adverse conditions (i.e., inadequate anchors distribution, low anchor density, hardware heterogeneity and fluctuating RSSI). In addition, the Author demonstrated the feasibility and benefits of our proposed approach and enlist its limitations and future research avenues to improve its performance.

1.5 Thesis outline

The contributions and results presented in this thesis correspond to the outcomes of the scientific works conducted by the Author at the Institute of New Imaging Technologies, University Jaume I (Castellón, Spain) and Electrical Engineering Unit, Tampere University (Tampere, Finland), between 2019 and 2022, which have been published in international journals [3, 21], proceeding of international conferences [4, 6, 22] and open access repositories [23].

This thesis is organized into six chapters. The first chapter covers the introduction and research motivations and details the research questions, objectives, methodology, and contributions of the research. The remaining chapters are organized as follows:

Chapter 2 introduces the concept of CIPSs and presents an overall review of latterly CIPSs through a systematic review. Considering the system's architecture, infrastructure, technologies, techniques, methods, and evaluation aspects implemented on CIPSs. In addition, the current trend and the main gaps in CIPS research are highlighted.

Chapter 3 describes the mobile device-based BLE databases for non-collaborative and collaborative indoor positioning approaches testing, as well as the methodology regarding their data collection and the indoor scenarios used (office and lobby). Additionally, it describes the BLE and Wi-Fi radio maps created to perform lateration and fingerprinting.

Chapter 4 describes and analyzes the traditional non-collaborative methods to estimate distance (i.e., based on LDPL model and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-NN), as well as the BLE-RSSI propagation in indoor environments. Moreover, it presents two novel solutions to improve distance and positioning accuracy.

Chapter 5 describes the proposed BLE-Collaborative Indoor Positioning System (CIPS) based on mobile devices and presents and analyzes the results of evaluating the performance of the system against non-collaborative approaches (i.e., RSSI-lateration and fingerprinting–k-NN).

Chapter 6 contains the conclusions, limitations, and recommendations for further research directions.

2 COLLABORATIVE INDOOR POSITIONING SYSTEMS: A SYSTEMATIC REVIEW

The potential of Collaborative Indoor Positioning Systems (CIPSs) to enhance the performance of traditional (non-collaborative) indoor positioning systems has generated a constant and growing interest in their research and development. Unlike to outdoor environments, where navigation and positioning systems rely primarily on Global Navigation Satellite System (GNSS), [1, 24], a vast diversity of technologies, techniques, and methods are implemented in collaborative positioning systems for indoor environments. This chapter introduces the main concepts of Indoor Positioning Systems (IPSs) and CIPSs and their differences, summarizes the most relevant classifications for IPSs, and presents an overall review of CIPSs through a systematic review. The review, carried out in the initial phases of our research work, includes 84 articles published between 2006 and 2020. For the sake of completeness of this PhD dissertation, an update was conducted, which includes 15 additional articles published between 2020 and 2022. Even though 7 articles from 2020 were already included in the systematic review, the search queries were conducted in January 2020, so a recent search revealed 5 more articles in 2020. The classification, analysis, and discussion of articles focused on the system's architecture, infrastructure, technologies, techniques, methods, and evaluation metrics implemented on CIPSs. In addition, the current trends, challenges, and main gaps in CIPS research are highlighted, and the evolution of CIPSs over time is studied.

2.1 Indoor positioning systems

An IPS is a working system that combines indoor positioning technologies, techniques, and methods to provide the position of objects or people inside closed environments [25]. The IPSs can be as straightforward as the use of k-Nearest Neighbors (k-NN) algorithms in fingerprinting approaches to estimate position [26, 27] or more sophisticate and complex as sensor fusion data approaches that combine diverse technologies (e.g., Inertial Measurement Unit (IMU) and Bluetooth Low Energy (BLE)), methods (Pedestrian Dead Reckoning (PDR) and fingerprinting) and data through Kalman Filter (KF) algorithms [28, 29]. Nevertheless, its design is very context-dependent and is centered on three key elements – technologies, techniques, and methods.

The technologies used on indoor positioning are the heart of the IPSs and could be considered as a context measure for the deployment –i.e., the desired positioning accuracy. Unlike outdoor positioning, mainly based on satellite constellations that transmit, in Line-of-sight (LOS), synchronized and time-stamped Radio Frequency (RF) signals to receivers, the technologies of indoor positioning are diverse due to heterogeneity of scenarios and involve a wide amount of technologies. For example, technologies relying on sound and light as ultrasound [30] and Visible Light Communication (VLC) [31], force/acceleration (IMU [32]), RF as 5G [33], LTE [34], RFID [35], BLE [36], Ultra-wide band (UWB) [37] among others. Concerning the positioning techniques, they specify the type of information (e.g., data or measurement) used to estimate the position. To mention some examples, Angle of Arrival (AoA) processes the angle and direction of received signals, Time of Arrival (ToA) uses the signal time-of-flight from the transmitter to the receiver, and Received Signal Strength Indicator (RSSI) considers the signal strength measured by the receiver. The methods correspond to the specific algorithm implemented to process the information available to estimate the position.

A broad variety of methods are proposed in the literature, which can include singular variants of widely used methods, such k-NN, or methods briefly described which are identified mainly for their technique used, such as fingerprint-based methods. Additionally, the methods can be linked to a specific technology or technique, for example, the PDR for inertial measurements, or to general algorithms which belong to a well-known set of algorithms, such as machine learning for classification. To summarize, despite the fact that an IPS can be a straightforward system, such as a system for IEEE 802.11 Wireless LAN (Wi-Fi) signals based on fingerprinting–k-NN algorithm [38, 26, 27], several systems are complex, as for example, systems based on sensor fusion [28, 29].

Considering the place where the positioning algorithms are executed in the IPS, we can distinguish two types of computational architectures: based on a server (e.g., Where@UM [39]) and the server-free or stand-alone (e.g., *AnyPlace* [40]). On the one hand, the server-based architecture processes the information (e.g., raw data) provided by each device in a server, which estimates the position without using information from others devices. On the other hand, the server-less architecture estimates the position locally in the devices, which contain their own information to self-determine their position. Device position estimation is performed considering the information provided by the device regardless of whether the architecture is server-based or stand-alone.

There are typically two types of infrastructure, infrastructure-free/infrastructure-less and infrastructure-based IPS, according to the literature [41, 42, 43, 44]. From one side, the infrastructure-less IPSs, such as IPSs based on magnetic field [44], do not need the deployment of any infrastructure in the vicinity to operate. Contrarily, the infrastructure-based IPSs requires physical elements placed in the environment (e.g., UWB beacons) to operate [41, 43, 44]. Some authors defined an intermediate class called opportunistic IPS [45, 46, 47] to distinguish between IPS where infrastructure has to be purposefully installed and IPS that exploit the available infrastructure, known as IPSs based on signals of opportunity. An example of the last one is the IPSs based on existing Wi-Fi Access Points (APs), where it is not necessary to modify the environment to allow the operation of the positioning system. Opportunistic approaches are not treated as a different group in this thesis. Additional information about non-collaborative IPSs (traditional IPSs) can be found in [48], [49] and [50].

2.1.1 Technologies

From the perspective of indoor positioning technologies, there is a wide range of technological solutions presented by the research community, which aim to increase the performance of positioning systems in various scenarios and applications. Plenty of technologies for indoor positioning have been extensively documented, categorized, utilized and assessed in the literature [51, 52, 48, 53, 54, 1]. Nonetheless, there is no unique classification that encompasses all of them. Within the most popular published classifications of technologies that allow us to illustrate the heterogeneity of criteria used for classification, we can find, for example, the classification of Gu, Lo, and Niemegeers [54], which divides the technologies into six categories depending on the type of signal measured, but only covers wireless personal networks; Mautz [52], under the premise of systems' performance with a similar type of sensors can be readily evaluated and compared, categorize the technologies in thirteen sensor technologies; likewise, Mendoza-Silva, Torres-Sospedra, and Huerta [48], based on the kinds of sensors used, identifies and describes ten groups to encompass the most often used technologies in IPSs encountered in their meta-review; Basiri, Lohan, Moore, Winstanley, Peltola, Hill, Amirian, and Silva [1] in their review identifies twenty positioning technologies, which features were summarized and specifies, in addition, classify the most appropriate technologies available in the market for Location-based Services (LBS) applications. The classifications mentioned above are enlisted in Table 2.1.

Table 2.1 Summary of proposed classification for indoor positioning technologies. Source [3].

Gu, Lo, and Niemegeers [54] (2009)	Mautz [52] (2012)	Basiri, Lohan, Moore, Winstanley, Peltola, Hill, Amirian, and Silva [1] (2017)	Mendoza-Silva, Torres-Sospedra, and Huerta [48] (2019)
•Infrared •Vision-based •Magnetic •Audible Sound •Ultrasound •Radio Frequency	•Infrared •Camera •Magnetic Localization •Sound •INS •UWB •WLAN/WiFi •RFID •Tactile and Combined Polar Systems •High sensitive GNSS / Assisted GNSS •Pseudolite •Infrastructure systems •Other RF(Cellular Networks, Zigbee, Radar, DECT Phones, Digital TV, FM radio)	•Infrared Market or reflective element •Infrared Light image feature matching •Light image feature matching •Light image market •Magnetometer •Sound •UWB ToF •WiFi RSS •WiFi ToF/AoA •RFID active •Bluetooth RSS •Tactile on user device •Tactile Environment •Tactile Odometer •Pseudolite •GNSS •Electromagnetic Systems •Barometer •Mobile Network	•Light •Computer Vision •Magnetic Field •Sound •Dead Reckoning •UWB •WiFi •RFID and NFC •Tactile Odometer •BLE •Other Technologies (Cellular Network, ZigBee, 5G)

2.1.2 Techniques

The techniques implemented on the IPS are mostly determined by the indoor positioning technology used. In addition, the type of technique implemented in the system has a significant impact on its performance. That is, even though the technology and test circumstances are the same, the performance of the IPS might vary significantly depending on the technique used. As a result, there are several studies that categorize, summarize, and characterize IPSs techniques [51, 48, 53, 54, 1]. Techniques, like technologies, have been classified from several perspectives. Within the most popular published classifications of techniques that allow us to illustrate the heterogeneity of criteria used for classification, we can find, for example, Liu, Darabi, Banerjee, and Liu [51] in their classification considers three groups, the first group called triangulation, composed of two subgroups lateration and angulation, which considers the geometric properties used to determine the target position; scene analysis group, which uses fingerprints measurements, and proximity group, which uses relative location data; Gu, Lo, and Niemegeers [54] divides the techniques into four groups, one of which corresponds to a new group, vision analysis, which uses images obtained from one or more points; Zafari, Gkelias, and Leung [53] present directly eighth techniques instead of creating subgroups, six considering range measurements, one considering fingerprint, and one considering channel attributes; Mendoza-Silva, Torres-Sospedra, and Huerta [48] provide four techniques, one considering the AoA and the others based on ranging (i.e., ToA, Time Difference of Arrival (TDoA) and Received Signal Strength (RSS)). The classifications mentioned above are enlisted in Table 2.2.

2.1.3 Methods

Indoor positioning methods/algorithms are precise sequential steps to follow to calculate/estimate the location of a target [54]. The methods are fundamentally tied to the technologies and techniques applied to the IPS. In the literature, there are numerous scientific works [55, 44, 56, 57, 50], which describe and detail the methods both generically and in detail, based on a specific technique or/and technology. Regarding the latter, the most popular published classifications of methods that allow us to illustrate the heterogeneity of criteria used for classification, we can find, for instance, He and Chan [55] focus on methods applied to Wi-Fi fingerprinting based

Table 2.2 Summary of proposed classification for indoor positioning techniques. Source [3].

Liu, Darabi, Banerjee, and Liu [51] (2007)	Gu, Lo, and Niemegeers [54] (2009)	Zafari, Gkelias, and Leung [53] (2019)	Mendoza-Silva, Torres-Sospedra, and Huerta [48] (2019)
•Triangulation –Lateration *ToA *TDoA *RSS-based *RToF *PoA –Angulation - AoA •Scene Analysis •Proximity	•Triangulation –RSS –ToA –AoA •Fingerprinting •Proximity Location •Vision Analysis	•RSSI •Channel State Information •Fingerprinting/Scene Analysis •AoA •ToA •TDoA •RToF •PoA	•AoA •ToA •TDoA •RSS

IPS and classify them into probabilistic or deterministic; Chen, Guo, Shen, and Cao [44] focus on methods based on Wi-Fi–RSS and categorize them into two groups, methods based on geometry and fingerprinting; Guvenc and Chong [56] in their review focus on methods applied to ToA-based localization and classify them into two groups, methods for Non-line-of-sight (NLOS) scenarios and LOS scenarios; Yassin, Nasser, Awad, Al-Dubai, Liu, Yuen, Raulefs, and Aboutanios [57], on the other hand, provides a broad review of three methods based on proximity, triangulation, and scene analysis techniques.

It should be noted that the classifications mentioned above are not based on the raw data gathering stage (where the data to process is collected); they are based only on the IPS operational stage. For example, RADAR [38], which is considered the first fingerprinting method, can still be used in new systems, regardless of how the data is collected, such as automatically from unlabeled samples [58], after interpolating a reduced radio map [59], through crowdsourcing [60], or based on an advance path-loss model [61] that create the data. The classifications mentioned above are enlisted in Table 2.3.

Table 2.3 Summary of proposed classification for indoor positioning methods. Source [3].

Guvenc and Chong [56] (2009)		He and Chan [55] (2016)	Yassin, Nasser, Awad, Al-Dubai, Liu, Yuen, Raulefs, and Aboutanios [57] (2017)	Chen, Guo, Shen, and Cao [44] (2017)
In LOS scenarios •Maximum likelihood (ML) –ML –Two-Step ML –Approximate ML •Least Squares (LS) –Non-Linear LS –Linear LS through Taylor's Series Expansion –Contrained Weighted LS	In NLOS scenarios •Maximum likelihood (ML) –ML utilizing NLOS Statistic –Identification & Discard based ML •Least Squares (LS) –Weighted LS –Residual Weighting •Constrained Localization –Constrained LS with Quadratic Programming –Constrained LS with Linear Programming –Geometric Constrained Localization –Interior Point Optimization •Robust estimator –M-estimator –Least Median of Squares	•Deterministic –Euclidean Distance –Cosine Similarity –Tanimoto Similarity –K Nearest Neighbors –Support Vector Machine –Linear discrimination Analysis •Probabilistic –Maximum Likelihood –Bayesian Network –Expectation-Maximization –Kullback-Leibler Divergence –Gaussian Process –Conditional Random Field	•Triangulation-based •Scene Analysis-based •Proximity-based	•Geometric-based •Fingerprint-based

2.2 Collaborative indoor positioning systems

The literature, based on the role played by diverse actors/users in IPSs, divides the IPSs into two primary types, the non-collaborative and collaborative [15, 18, 17, 19]. Both terms are related to the operational phase, where the position is estimated, and not to the data collection phase, for example, the construction of a fingerprint-based database. On the one hand, systems whose schemes do not take into account the involvement of other actors/users in their positioning algorithms are called non-collaborative IPSs [19]. On the other hand, systems that determine the position as a result of the indirect/direct interoperability between nearby actors/users or several IPSs are called CIPSs. It is worth highlighting that collaborative approaches are not related to approaches that rely on data or sensor fusion. While CIPSs provide a single user's position based on schemes that uses independent actors/users, which exchange information and relative distance computed between them [62, 63, 18, 19, 64], sensor fusion in order to provide a single user's position fuses data from several sensors from a single user [65, 66, 67, 68].

Collaborative systems heavily exploit technological developments and techniques and methods created specifically for conventional IPS to compute the position of collaborative nodes in CIPSs. In addition to exploiting these technologies for position estimation, CIPSs use them to enable information sharing between nodes. For example, RF-based technologies such as cellular networks, BLE, Wi-Fi, etc. have a great variety of protocols for communication. Among the most commonly used in BLE andWi-Fi, we can mention iBeacon and 802.11n as examples. CIPSs methods are quite varied. Nonetheless, within that diversity, we have well-known methods such as maximum likelihood and Least Square (LS) [69], which are based on the popular non-bayesian and belief propagation approaches.

The computational architecture, in collaborative approaches, is more elaborate than the non-collaborative contra-part because the positioning algorithm includes the information provided by neighboring devices. Typically, in CIPSs, we can distinguish centralized and decentralized architectures. In the first [57, 70, 19], a single node of the network is used to process the information gathered and sent by the other members of the network to estimate the position of all of them. In contrast, in a decentralized architecture [52, 57, 18, 70, 19, 43], the function of collaborative nodes is to collect and share important data (raw or processed), as well as to process and compute them to estimate their own position. The final device's position is determined considering the information provided by the own device and its neighbors regardless of whether the architecture is centralized or decentralized.

As part of the state-of-the-art (SOTA), we present a representative case of CIPS in Figure 2.1. Within the collaborative scenario, we can observe 5 different devices, each of which uses different positioning approaches to estimate its position, which adds heterogeneity to the indoor positioning scenario. The CIPS is a compound of a non-collaborative and a collaborative part. In the first one, each user estimates its position based on technology, technique, and method. User 1 estimates its position based on BLE, RSSI, and weighted centroid; User 2 based on the magnetic field, magnetic field fingerprint, and likelihood; User 3 based on UWB, ToA, and multilateration; and Users 4 and 5 based on Wi-Fi, fingerprinting, and k-NN. The estimated position and its level of uncertainty are represented by the blue ellipses under each user. In the collaborative counterpart, the five users use 5G Device to Device (D2D).

In order to exemplify how the users' collaboration enhances the estimated position (improved position represented by red ellipses), we present two CIPSs cases:

- The first case focused on improving the position accuracy of User 5, who presents significant uncertainty, applying an Extended Kalman Filter (EKF), which combines ranging data from Users 2 and 3.

- The second case focused on estimating the position of User 4. User 4 is out of range of Wi-Fi area and cannot estimate its own position. So, User 4's position is estimated using an EKF, which combines ranging data from 3 Users (1–3).

CIPSs and non-collaborative IPSs differ in the way they use technologies. The former uses technologies to exchange information and estimate position between users, and the non-collaborative IPSs uses the technologies only for position estimation. In addition, the methods used in CIPS estimate the position not only taking into account the data/information of individual users but also those of neighboring users.

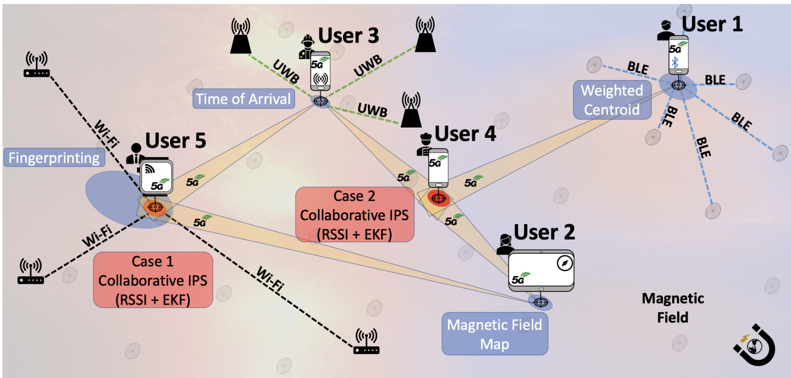


Figure 2.1 Example case of a heterogeneous CIPS configuration. Source [3].

2.3 Research methodology of systematic review

Our proposed CIPSs systematic review follows the directions specified by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) [71]. The PRISMA guidelines, applied to our review, consist of the following steps:

- **1st step:** Formulation of a group of research questions, which specify and delimit the scope of the review;
- **2nd step:** Formulation of a group of inclusion and exclusion criteria, aligned with the study's objectives and limits stipulated by the research questions, to

help us identify the relevance of each research article under consideration;

- **3rd step:** A thorough research articles selection procedure is conducted. First, appropriate search queries were created and used to retrieve all relevant articles. In our case, Web of Science and Scopus research engines were used. Then, to get the final collection of relevant articles, the found records are combined, duplicates are eliminated, and analyzed considering the criteria formulated in **2nd**, and
- **4th step:** The papers are classified and their main characteristics are extracted, mapped, and evaluated.

Sections 2.3.1 and 2.3.2 detail the formulated research questions and criteria considered in the methodology to carry out our systematic review, respectively. Section 2.3.3 describes the selection process, and Section 2.3.4 presents the classification of studies.

2.3.1 Research questions

The systematic review's goals include evaluating the research works in CIPSs providing a summary of them and presenting their findings. These goals led to the formulation of the following research questions, which are aligned with the main **RQ1** stated in Section 1.2:

> **RQ1**$_{rev}$: What are the infrastructures, architectures, technologies, techniques, and methods (also called algorithms) used in/for CIPSs?
>
> **RQ2**$_{rev}$: In which combination are technologies, techniques and methods used in/for CIPSs?
>
> **RQ3**$_{rev}$: How have CIPSs been evaluated and what are the metrics used?
>
> **RQ4**$_{rev}$: What are the limitations, current trends and gaps, and future research avenues that have been reported?

The principal purpose of our review is stated in **RQ1**$_{rev}$. Despite the fact that infrastructures, architectures, technologies, techniques, and methods have been approached and described from the IPS point of view, in our review, we approach them from the perspective of collaborative systems. In addition, we highlight the similarities and differences between collaborative and non-collaborative systems. **RQ2**$_{rev}$

is focused on gaining an understanding of how the various technologies, techniques, and methodologies are used together since they are the pillars of CIPS. The $\mathbf{RQ3}_{rev}$ aims to provide the assessment metrics that were utilized and the kind of evaluations that were conducted in CIPS, and their proportion according to the information collected. The $\mathbf{RQ4}_{rev}$ aims to give the scientific community avenues for future study in CIPS while also providing a comprehensive view of trends, open issues, and limitations.

The research sections where the research questions are addressed are listed as follows:

$\mathbf{RQ1}_{rev}$: Result Sections 2.4.2 & 2.4.4 and Discussion Sections 2.5.1 & 2.5.2.

$\mathbf{RQ2}_{rev}$: Result Section 2.4.4 and Discussion Section 2.5.2.

$\mathbf{RQ3}_{rev}$: Result Sections 2.4.5 & 2.4.1 and Discussion Sections 2.5.3.

$\mathbf{RQ4}_{rev}$: Discussion Section 2.5.4 and Conclusion Section 2.7.

2.3.2 Inclusion and exclusion criteria

The scientific works included in this review are evaluated considering the following inclusion and exclusion criteria.

2.3.2.1 Inclusion criteria

IC1: Any comprehensive, primary scientific paper authored in English and published in a peer-reviewed international conference proceeding or journal.

IC2: Any research article that directly proposes a collaborative indoor positioning system that considers people as the main users.

2.3.2.2 Exclusion criteria

EC1: Any publications that are not full articles (e.g., extended abstracts, posters, workshop publications), or are not main scientific papers (e.g., summaries, reports, patents), or are not published in a peer review international conference proceeding or journal (e.g., book chapters).

EC2: Any publications that do not consider as a primary study one or more CIPS to provide to the users' indoor position (e.g., outdoor positioning or non-collaborative approaches) or focus on non-human use cases (e.g., positioning systems for Unmanned Aerial Vehicle (UAV) or sub-aquatic vehicles).

EC3: Any publications that do not take into account the concept of collaboration as the action of collaborating with surrounding actors/users to determine their position(e.g., sensor fusion).

2.3.3 Study selection process

The selection process of relevant studies was carried out according to the guidelines of PRISMA. In the first phase, the identification phase, an exhaustive search of the articles was carried out using the search engines of the two largest scientific databases (Web of Science and Scopus) to discover possible works aligned with the research questions. For each search engine, similar search queries were provided, using a set of keywords combined through boolean operators according to the syntax requirements of each research engine. The search queries are shown in Table 2.4. Next, a screening process was performed, which first deleted duplicates and then screened the remaining articles' titles, abstracts, and keywords considering the criteria presented in Section 2.3.2. In the eligibility phase, the articles selected by the screening phase were thoroughly reviewed considering the inclusion and exclusion criteria to get a final collection of the studies included in the review. The PRISMA flow diagram of the study selection process, described above, is presented in Figure 2.2. As result of selection process, 84 articles [72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 17, 84, 85, 14, 86, 87, 88, 89, 90, 91, 92, 12, 93, 94, 7, 95, 96, 8, 97, 98, 99, 100, 101, 102, 9, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 41, 117, 118, 119, 120, 10, 121, 122, 11, 118, 15, 123, 13, 62, 124, 63, 18, 64, 16, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138] were chosen for comprehensive analysis and inclusion in our review.

2.3.4 Classification of the studies

To classify the studies, we divided the CIPSs into a non-collaborative phase, a collaborative phase, and an overall system, which is a usual way to break down the CIPSs. In the non-collaborative phase, each individual node collects positioning-related data and (optionally) determines its position. In the collaborative phase, the nodes exchange positioning-related data and, based on the shared information, the

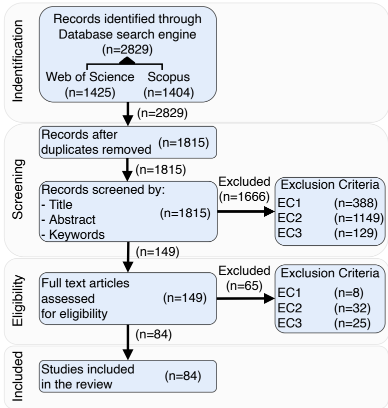


Figure 2.2 PRISMA flow diagram.

Table 2.4 Scopus and Web of Science search queries. Source [3].

Database	Input Query
Scopus	(TITLE-ABS-KEY (((Collabora* OR Coopera*) AND Indoor) AND (Position* OR Track* OR Locati* OR Locali* OR Navigat*)) AND LANGUAGE (english))
Web of Science	TS=((Collabora* OR Coopera*) AND Indoor AND (Position* OR Track* OR Locati* OR Locali* OR Navigat*))

position is computed. The overall system organizes and combines the system's non-collaborative and collaborative parts. Aligned with our review's aims and research questions, the complete classification scheme is illustrated in Figure 2.3. The following subsections describe each of its parts in detail.

2.3.4.1 Non-collaborative and collaborative phase

The description of the technologies, techniques, and methods categories used in our classification is presented below:

- **Technologies.** On the one hand, it includes technologies used to calculate the position in the non-collaborative part and, on the other hand, for collaboration and information exchange between nodes/users. For any part (collaborative and non-collaborative) of a CIPS, the same or different technologies can be used. IMU, laser, and VLC are some examples of technologies used in the non-collaborative part, while Wi-Fi and BLE are examples of technologies that

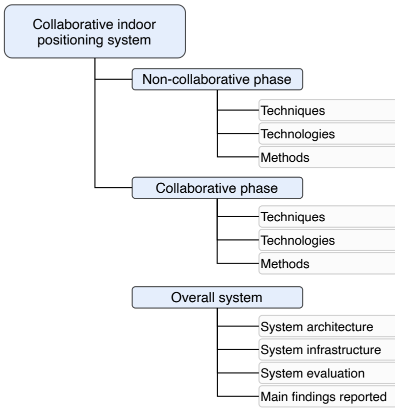


Figure 2.3 Structure of classification of studies.

can be used in both.

- **Techniques.** This category considers positioning techniques, for example, AoA, and Uplink Time-Difference-of-Arrival (UTDoA) used in the non-collaborative part. Also, it includes the techniques that allow to the nodes/users to collaborate between them, for example, Two-way Ranging (TWR), positioning data sharing, among others. A technique is defined as the procedure describing how particular technologies and information (e.g., raw or processed data) are arranged and used to accomplish positioning.
- **Methods.** The methods, also known as algorithms, cover the mathematical methods that compute the nodes/users' position, and also those that include the collaboration between nodes/users to accomplish positioning. In the collaborative part, some examples of methods are multidimensional scaling, bayesian filter, and EKF and in the non-collaborative part ranging, PDR, and multilateration. A method is defined as a set of logical steps or rules to be used in computations to estimate a position.

2.3.4.2 Overall system

The characteristics of the system are encompassed by the overall system, which classifies them into four dimensions, namely architecture, infrastructure, evaluation, and main findings of the system. Each dimension is described as follows:

- **System architecture.** This dimension corresponds to the kind of architecture used to process the data in the CIPSs. Specifically, in this review, we consider two types, distributed and centralized.

- **System infrastructure.** This dimension refers to the equipment installed in the surroundings needed to make the CIPS work. For example, devices such as BLE anchors, Wi-Fi APs, UWB anchors, and other dedicated hardware are deployed in the positioning scenarios.
- **System evaluation.** This dimension corresponds to the way that the performance (e.g., position accuracy, robustness, position precision, etc.) of the system is assessed, such as by simulation, experiments, or both.
- **Main findings identified.** A classification of the primary findings identified in the CIPS studies is presented. The findings are classified with respect to the evaluation metrics used on the position precision and accuracy, energy consumption, computational complexity, and robustness of the system; general concerns, which are not focused on a specific technology, technique, method, architecture, or infrastructure; systems' limitations and future research directions.

The overall structure of our classification scheme presents some similarities with those previously published (see Sections 2.1.1, 2.1.2 and 2.1.3). Nevertheless, we do not aim to classify technologies, techniques, and methods. Instead of that, we thoroughly collect the technologies, techniques, and methods discovered throughout our review to classify the articles based on their use.

2.4 Results of reviewed studies

2.4.1 Distribution of CIPSs over time and their evaluation metrics

The distribution of the 84 articles contained in our review and their evaluation metrics are depicted in the stacked bar graph in Figure 2.4(**a**). Articles containing multiple evaluation metrics are depicted by vertically split stack bars. For instance, the bar for 2013 contains 5 articles, of which 3 fully evaluated the position accuracy, 1 evaluated robustness and position accuracy, and 1 computational complexity and positioning accuracy. Additionally, the pie chart shows the accumulated percentage of evaluation metrics.

In general, the number of publications increased from 2006 to 2020, as verified by the trend line drawn on the graph (light gray). Within the first five years, 2006 to 2010, we notice a limited quantity of publications. The number of publications has increased gradually but steadily in the years afterwards, with significant increases in the years 2011, 2015, and 2019. These specific increments considerably raised the average to about 7 articles within the period.

From the pie chart, we can observe that positioning accuracy (cyan color) is the most common evaluation metric, applied in the 84 articles, both as an individual metric (69% accumulated) and parallel with others (31% accumulated). In the second place, computational complexity evaluation with 15.5% (individual) + 3.6% (in parallel with robustness). Then, robustness evaluation with 6% (individual) + 3.6% (in parallel with computational complexity). Finally, the evaluation metrics energy with 3.6% and position precision with 2.4%.

46% (39 articles) of all papers included in the review have been published in the last 4 years. In general, we cannot identify a clear trend in the metrics used to evaluate the CIPS. However, we can observe a growing interest in computational complexity evaluation, also in parallel with robustness. But it is premature to consider it a trend due to the small number of articles with such evaluation.

It should be noted that the number of publications in 2020 must be carefully interpreted, as the database queries were launched on January 8^{th} 2021, and at that time, not all 2020 records were fully included in the databases.

2.4.2 Architecture and infrastructure

The distribution over time of the types of architecture and infrastructure used in the CIPSs, reported in the 84 articles of our systematic review, are illustrated in Figure 2.4(b) and Figure 2.4(c), respectively.

Regarding the architecture, we identified two principal types, decentralized and centralized (see bars and segments in purple and blue of Figure 2.4(b), respectively). The decentralized architecture is the most common, used by 44.05% of articles, followed by the centralized one, used by 26.19%. 23 of the evaluated articles (27.38%) did not describe the architecture used. In red and green in Figure 2.4(b), we can see the two unique articles that use hybrid and interchangeable architecture approaches, respectively. Specifically, one presents a hybrid approach that combines both architectures [89], and the other an approach that can interchangeably use either of the two architectures [85].

Analyzing the results of Figure 2.4(b) chronologically, we observe that during 2006-2014 the decentralized architecture was the prevailing architecture (used 4 times more than centralized). Then, from 2015 to 2017, there was a rise of papers using centralized architecture (centralized was used approximately 2 times more than decentralized). In 2018 and 2019, the decentralized architecture shows a significant growth in the number of papers, while the centralized architecture drops, inverting the proportion between centralized and decentralized (centralized was used approximately 2 times more than decentralized). The interchangeable and hybrid architecture approaches were introduced in 2012 and 2013, respectively.

Regarding the infrastructure, we identified two principal types of CIPSs, CIPSs with infrastructure and infrastructure-less (see bars and segments in green and red of Figure 2.4(c)). The CIPSs infrastructure-less are the most relevant, with a 63.1% (considering 14 systems based on signals of opportunity of 53), followed by the infrastructure-based with 28.57%. The 8.33% did not provide information about the infrastructure used. Considering the results chronologically, we note that infrastructure-based systems were first introduced in 2011 and then presented a slow growth, however, in recent years, their use has intensified. In all years, the amount of papers based on CIPSs infrastructure-less is greater than the infrastructure-based, with the exception of 2016 presenting an equal amount of papers, and 2019, where the amount of infrastructure-based systems (8 papers) outnumbers the infrastructure-less (6 papers). It is not clear if this trend will persist in the upcoming years.

2.4.3 Non-collaborative technologies, techniques, and methods

Figure 2.5 illustrates a Sankey diagram, which, from left to right, presents the non-collaborative technologies, techniques, and methods. The non-collaborative part uses them to determine the position, considering the self-collected data of each node/user instead of the data collected collaboratively. The aforementioned dimensions were used to classify and categorize the papers of the review, each category is sorted in descending order. Next to each category's name of each dimension a percentage is added (e.g., Wi-Fi (53.5%), which corresponds to the technologies' dimension of Figure 2.5). The percentage shows how many papers out of the whole set use a certain technology, technique, or method. It should be pointed out that the CIPS presented in a paper may involve many technologies, techniques, and methods, so,

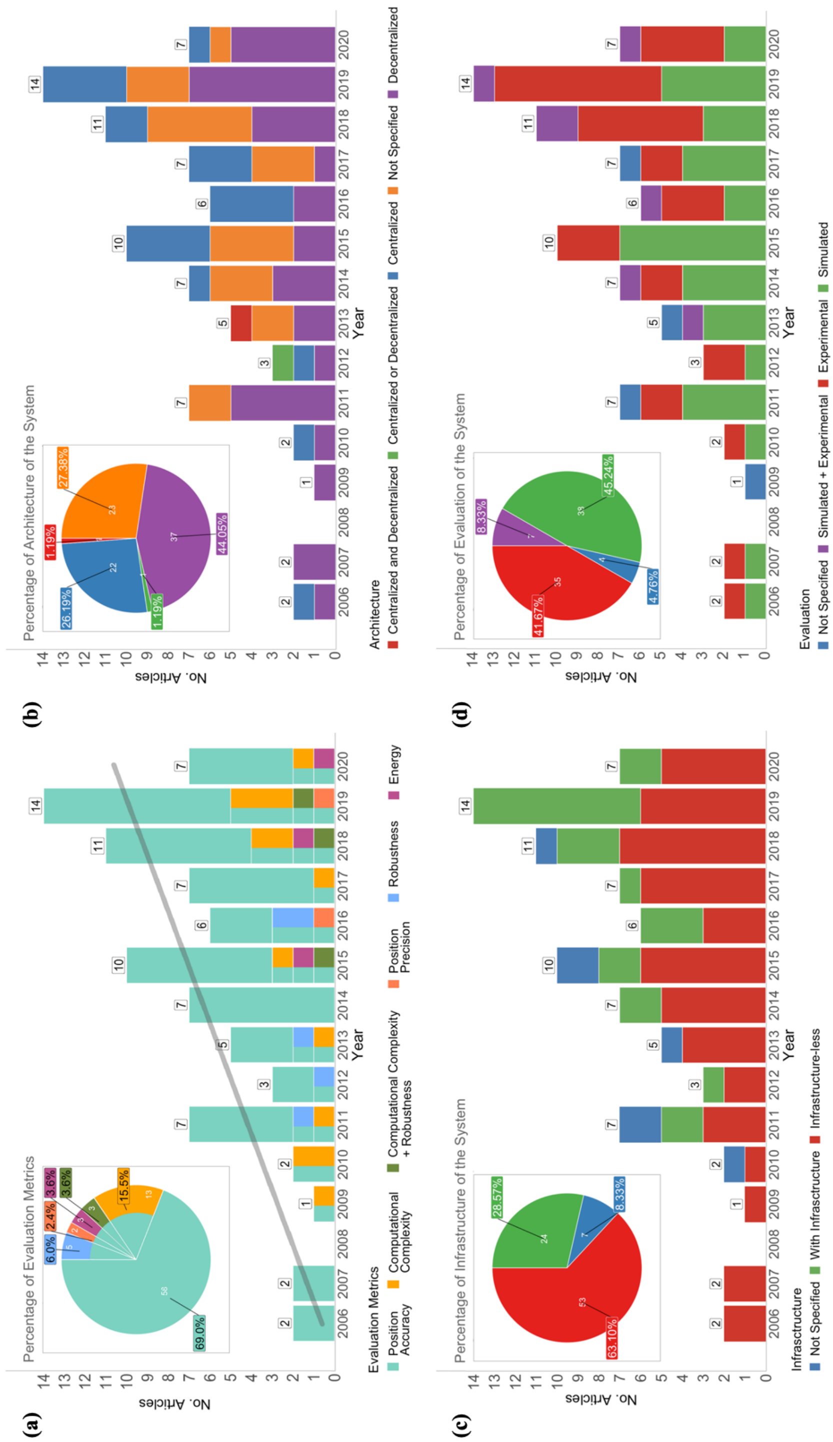


Figure 2.4 Distribution of CIPSs over time (**a**) Evaluation metrics. (**b**) Systems' architecture. (**c**) Systems' infrastructure. (**d**) Systems' evaluation. Source [3].

the sum of percentages, in each dimension, may exceed 100%. In addition, the combination between technologies and techniques and between techniques and methods is linked through horizontal lines/bands. The band colors are determined by the technique, instead of method or technology, since the technique is the dimension that connects the technologies and methods. It is important to stress that several papers did not report the precise method employed. So, instead of categorizing them just as "unknown", we categorize them considering their technique, to provide extra information by adding the suffix "-based" (e.g., RSSI-based methods).

An overall statistics of the non-collaborative technology, technique, and method used and their correlation between them is shown in Figure 2.5. From the figure, we notice that twelve diverse technologies are used. On one side, listed in descending order, we have that the most used are Wi-Fi, IMU, and UWB with 53.5%, 30.9%, and 15.4%, respectively. On the other side, the lesser used are Radio-Frequency Identification (RFID), 5G, IEEE.802.15.4a.CSS, VLC, Long-Term Evolution (LTE), Bluetooth, with a 2.3% each, and camera, laser+compass, and hybrid sensors with a 1.1% each. Additionally, nine of the total technologies used are considered in only one or two articles. Under the Wi-Fi technology category, we included the Wireless Sensor Network (WSN) based on Wi-Fi technologies, Wireless Application Service Provider (WASP) and Wi-Fi WLAN and direct.

Under the technique dimension, ten diverse techniques are identified. On the one hand, listed in descending order, the most studied are RSSI, Dead Reckoning (DR), fingerprinting, and Time of Arrival/Flight (ToA/ToF) with 36.9%, 30.9%, 23.8%, and 11.9%, respectively. On the other hand, the lesser are TDoA, TWR, AoA with 4.7%, 3.5%, and 2.3% respectively, and QR code, hybrid techniques, and UTDoA with a 1.1% each. Also, we identified that four of the total number of techniques used are considered in only one or two studies.

Considering the method dimension, sixteen diverse methods were found. Within them, we can distinguish three groups. The first group corresponds to the most studied and jointly used in both, the collaborative and non-collaborative phases, which consists of PDRs and cooperative methods with 29.7% and 23.8%, respectively. Second, the moderately studied, consists of ranging, RSSIs-based methods, with 14.2% and 11.9%, respectively, and fingerprinting-based methods and k-NNs, with 9.5% each. Finally, the less frequently studied, consists of multilateration, geometric ranging, trilateration with 4.7%, 3.5%, and 2.3% respectively, and QR code recognition,

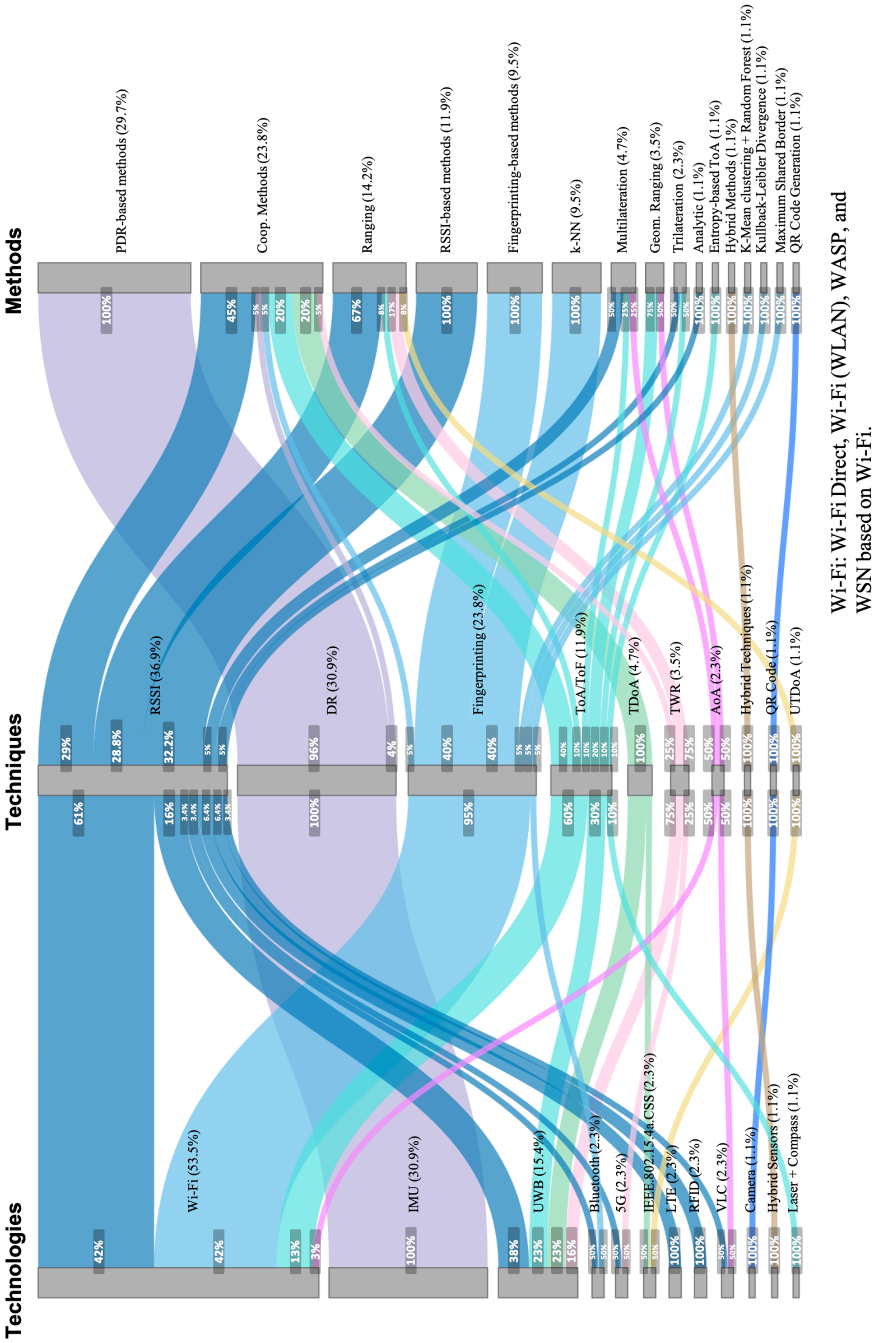


Figure 2.5 Statistical results and combination of non-collaborative technologies, techniques, and methods used in CIPSs. Source [3].

entropy-based, ToA/ToFs, analytic, hybrid methods, Kullback-Leibler divergence, k-means clustering + random forest, and maximum shared border with a 1.1% each. Furthermore, 43.75% of the methods used were only found in one study.

The sum of percentages of each dimension in Figure 2.5 is greater than 100%, so, we can deduce that certain works (14 works (16.6%)) use more than one positioning solution in the non-collaborative phase. In detail, the number of works that combined technologies are as follows: 8 works (Wi-Fi andIMU [89, 87, 91, 107, 112, 41, 10, 136]); 2 works (RFID and IMU [118], and UWB and IMU [133], and 1 work (Wi-Fi and Bluetooth [131]). Regarding the works that combine techniques, we identify 3 works (ToA/ToF and AoA+ [17], fingerprinting and RSSI [9], and ToA/ToF and RSSI+ [122]), which use Wi-Fi as main technology.

Figure 2.5, in addition to presenting the statistics within each dimension (technologies, techniques, and methods), also presents information about the combination between them. The most important observations are the following.

Technology dimension:

- Wi-Fi is the predominant technology, used in 53.5% of all papers. Wi-Fi is widely used in conjunction with two techniques: fingerprinting and RSSI, which each account for 42% of all papers based on Wi-Fi.
- IMU technology is the second most widely used technology (20.9% of all paper) and is combined exclusively with DR techniques and PDR methods, except for one combination with a collaborative algorithm.
- The technologies that have been joined with the most techniques were UWB and Wi-Fi (4 techniques each). The RSSI was the most often used technique for both technologies.

Technique dimension:

- DR technique was only implemented with (IMU technology).
- ToA/ToF and RSSI were combined with the greatest variety of technologies, 3 and 7 technologies respectively. Followed by fingerprinting, TDoA, TWR, and AoA, which are used in combination with 2 technologies each. The remaining techniques were used with only one technology.
- ToA/ToF and fingerprinting were combined with the greatest variety of methods, 6 methods each.

Method dimension:

- Cooperative methods and PDR-based are the most prevalent methods (53.5% of all papers). Then, the second most popular group is represented by RSSI-based, k-NN, fingerprinting-based methods, and ranging, which together with the most used are present in almost 98% of examined publications. Finally, the less common (10 remaining methods) are present in less than 20% of articles.
- A variety of techniques are combined with the cooperative and ranging methods. In detail, the 100% of techniques linked with the cooperative methods are listed, in descending order, as follows: RSSI with 45%, ToA/ToF, and TDoA with 20% each, and fingerprinting, DR, and TWR with 5% each. Regarding the techniques linked with ranging method: the prevalent is RSSI with 67% and in less proportion TWR with 17%, following by UTDoA and ToA/ToF with 8% each.
- Artificial Intelligence (AI), which is mainly composed of 3 positioning methods, k-NN, which represent the 9.5% of examined articles, Kullback-Leibler divergence, and k-means clustering + random forest with 1.1% of examined articles each.
- Due to the particularity of the methods, 7 of the 16 were used only once, only in the works that proposed them.

2.4.4 Collaborative technologies, techniques, and methods

Figure 2.6 illustrates a Sankey diagram, which, from left to right, presents the collaborative technologies, techniques, and methods. In the collaborative part, the sensor's data is exchanged between neighbors (node/actors), and the position is collaboratively computed. The Sankey diagram is built considering the same logic used in Section 2.4.3.

From Figure 2.6, we clearly observe a widespread number of combinations between technologies, techniques, and methods with respect to the results presented in Figure 2.5. Furthermore, it is noted that the RSSI technique is combined with a large number of technologies and is the most dominant.

In the collaborative phase of CIPSs, we identified twelve collaborative technologies. Sorting the identified technologies in descendant order, we have that the most popular are Wi-Fi, UWB, and Bluetooth with 41.6%, 23.8%, and 19%, respectively.

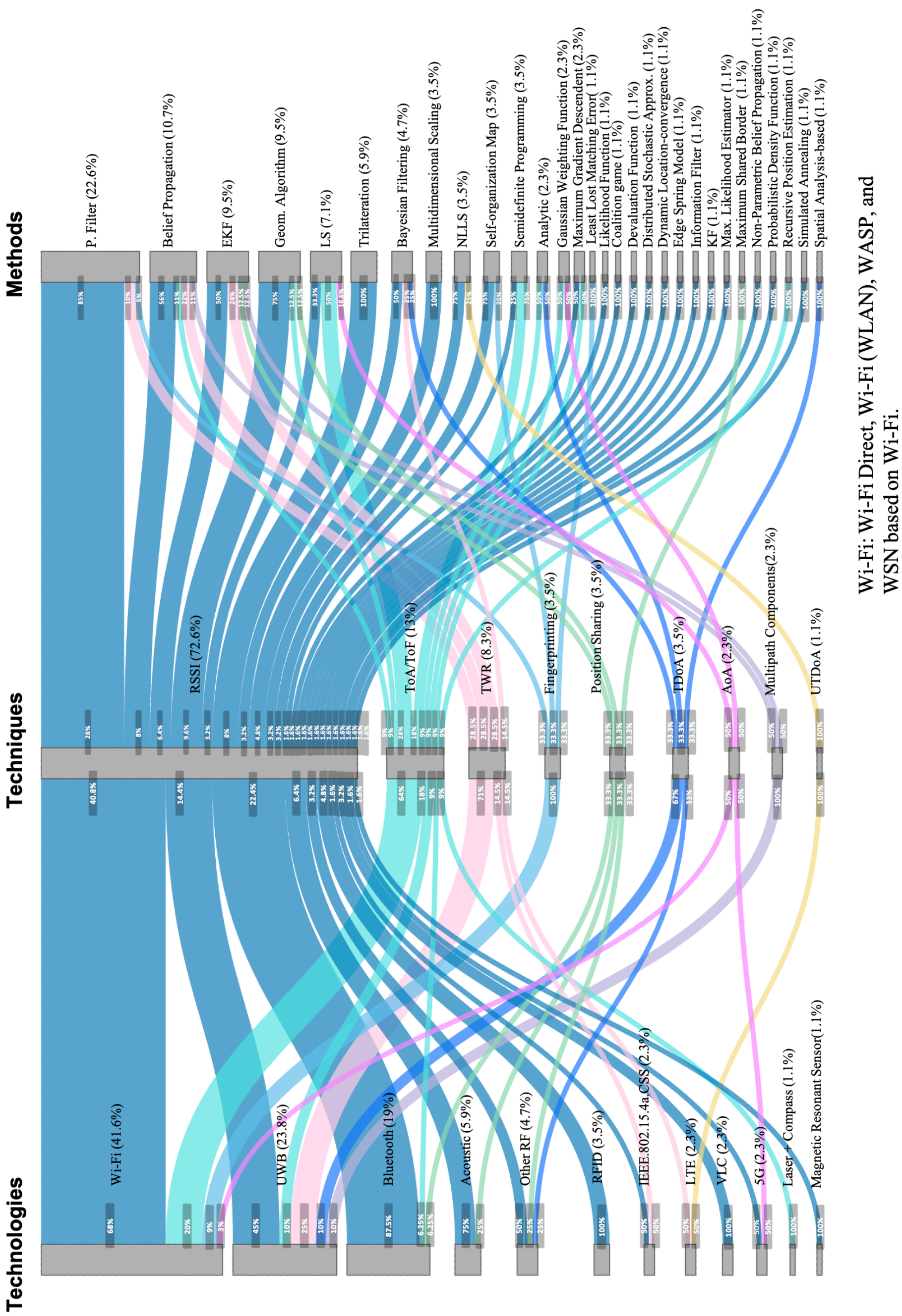


Figure 2.6 Statistical results and combination of collaborative technologies, techniques, and methods used in CIPSs. Source [3].

The remaining technologies, presented on five or less papers, are acoustic, other RF technologies, and RFIDs with 5.9%, 4.7%, and 3.5%, respectively, 5G, LTEs, IEEE.802.15.4a.CSS, and VLC with 2.3% each, and magnetic resonant sensor and laser+compass with 1.1% each.

Regarding the techniques, we identified nine collaborative techniques. Sorting the identified techniques in descendant order, we notice that the first and second prevalent techniques are RSSI and ToA/ToF with 72.6% and 13%, respectively. The remaining techniques are TWR with 8.3%, and position sharing, fingerprinting, and TDoA with3.5% each, and multi-path components and AoA with 2.3%, respectively, and UTDoA with 1.1%. Also, we encountered that six of the nine techniques are only mentioned in three or fewer articles.

We identify a wide range of 30 different collaborative methods. Within those widespread methods, the most commons are the particle filter with 22.6%, belief propagation with 10.7%, and geometric algorithms and EKFs with 9.5% each. The remaining methods are LS, trilateration, and bayesian filtering with 7.1%, 5.9%, and 4.7% respectively, and self-organizing map, semidefinite programming, Non-Linear Least Squares (NLLSs), and multidimensional scaling with 3.5% each, and edge spring model, spatial analysis-based, likelihood function, information filter, simulated annealing, dynamic location-convergence, coalitional game, non-parametric belief propagation, devaluation function, maximum likelihood estimator, distributed stochastic approx., kalman filter, maximum shared border, probabilistic density distribution, recursive position estimation, and least lost matching error with 1.1% each.

The sum of percentages of each dimension in Figure 2.6 is greater than 100%, so, we can deduce that certain works (9 works (10.71%)) use more than one positioning solution in the collaborative phase. In detail, the number of works that combined technologies are as follows: 6 works combine RSSI technique with two technologies (Bluetooth and acoustic [120], Wi-Fi and UWB [135], Bluetooth and Wi-Fi [9, 10, 131], and Wi-Fi and acoustic [107]) and 3 works combining Wi-Fi techniques with two technologies(RSSI+fingerprinting [91], AoA +ToA/ToF [17], and RSSI+ToA/ToF [122]). The technologies/techniques of those nine papers were combined by the collaborative positioning method.

Figure 2.6, in addition to presenting the statistics within each dimension (technologies, techniques, and methods), also presents information about the combination between them. The most important observations are the following.

Technology dimension:

- The Wi-Fi technology is the most commonly used, which is used in 41.6% of all papers. 68% of papers, that include Wi-Fi technology, are combined with the RSSI technique, which is the prevalent combination. To a lesser extent, the combinations with ToA/ToF, fingerprinting, and AoA with 20%, 9%, and 3%, respectively.
- Wi-Fi, UWB, and Bluetooth are the three most used technologies. They are combined with diverse techniques. In detail, as is shown in Figure 2.6, Wi-Fi is combined with 4 techniques (fingerprinting, RSSI, AoA, and ToA/ToF), UWB with 5 techniques (Multipath components, TDoA,RSSI, TWR, and ToA/ToF), and Bluetooth with 3 techniques (RSSI, position sharing, and ToA/ToF).

Technique dimension:

- The RSSI technique, which is present in 72.6% of the papers, is the prevalent collaborative technique. Also, the RSSI technique is combined with a large number of methods and technologies. The most popular combinations of RSSI technique are with Wi-Fi, Bluetooth, and UWB technologies with a 40.8%, 22.4%, and 14.4%, respectively, and the particle filter method with 28%.
- Almost all techniques have a wide variety of combinations with technologies and methods, with the exception of fingerprinting, which is combined just with Wi-Fi, and multipath components techniques, which is combined just with UWB. Regarding the methods, all techniques were combined with multiple methods, except the UTDoA, which is present in only one article.

Method dimension:

- Particle filtering is the most used method, which is used in combination with RSSI (85%), TWR (10%), and fingerprinting (5%).
- 20 of the 30 methods presented in collaborative methods correspond to AI. The prevalent methods are particle filter, belief propagation, least square, and bayesian filtering, which correspond to the 22.6%, 10.7%, 7.1%, and 4.7% of works, respectively.

- 16 out of 30 methods were used once and 6 out of 30 were used twice. The methods used only once were combined with a single technology and technique.

It should be noted that, in the CIPSs included in the systematic review, the authors only mentioned generic terms for Wi-Fi and BLE technologies in both collaborative and non-collaborative phases, without providing additional information about the specific version or frequency of these technologies used.

2.4.5 Evaluation of the systems

Knowing the systems' evaluation enables us a greater comprehension to analyze and compare the findings and results provided. The bar graph and pie chart in Figure 2.4(**d**) summarize the kind of systems evaluation identified in this review. The evaluation is classified as simulated, experimental, simulated + experimental, or evaluation not specified. We can observe, from the pie chart of Figure 2.4(**d**), that the percentage of systems evaluated through simulation (45.24%) and experimentally (41.67%) are very similar. Also, the percentage of systems evaluated using both experimentally and simulated (8.33%) and not specified (4.76%) are the least representative. From the bar graph, we can observe the evolution of the evaluation of the systems over the years. From 2006 to 2017 the evaluation through simulations was predominant. In recent years (2018–2020), evaluation through experiments has grown significantly at the same time that evaluation through simulations decreased, which originates a majority of experimental evaluations with a ratio of 2:1 approximately. Over the period of 2006-2020, simulated + experimental evaluations are rare.

2.5 Discussion

This section aims to thoroughly examine and discuss the articles included in our systematic review based on the results reported in Section 2.4 to determine the fundamental causes of the findings. Also, we highlight the gaps, limits, and future research directions, and, we elaborate on our responses to research questions $\mathbf{RQ1}_{rev}$–$\mathbf{RQ4}_{rev}$.

2.5.1 Architectures and infrastructure of CIPSs

In terms of architecture, we find that centralized architectures are less common than decentralized architectures. On the one hand, implementation and deployment challenges are frequently described in articles reporting on centralized CIPSs, which may discourage future use. The main problems reported are: the algorithms needed to solve the positioning problem cooperatively are quite complex [18, 118, 115, 92], massive data transmission between the centralized server and nodes, causing connectivity bottlenecks and delays [89, 92], scalability issues caused by concurrent users and computational load [118, 89, 84], and poor robustness against failure [118]. On the other hand, the decentralized architectures decrease the amount of shared raw data as well as the computational load by distributing the processes across all collaborative devices. For example, in decentralized architectures, each actor/node preprocesses the gathered data (e.g., estimating its position) and then transmits it, together with important information, to neighboring nodes. Regarding performance metrics, computational complexity metrics are the most used, mainly in centralized architectures, which use them to evaluate the level of computational optimization achieved [120, 121, 18, 126, 98, 79]. Other performance metrics (e.g., accuracy, precision) take a secondary role in the evaluation of architectures, as they are highly dependent on the technology, approach, and method used. To sum up, decentralized systems provide the same positioning accuracy while having fewer computational issues. This fact is one of the reasons why most systems prefer to implement decentralized architectures (44.05%) instead of centralized ones, especially during the past 4 years.

The kind of sensing technology used plays an important role in the selection between infrastructure and infrastructure-less approaches. Most of the positioning scenarios, used in the research, take place in existing buildings, sometimes reusing already deployed infrastructure for purposes other than positioning (signals of opportunity). Traditional indoor scenarios that are gaining popularity involve houses, offices [41, 120, 112, 104], and universities [7, 62, 41, 87, 90, 108, 117, 120, 10, 109] used to locate people. In such scenarios, unlike industrial or warehouse scenarios, which can afford the deployment of complex and robust infrastructures for positioning, the viability of deploying similar infrastructures is low due to the economic cost that it represents. In line with the aforementioned, our review demonstrates that, for

CIPSs, the infrastructure-less approaches are preferred (see Figure 2.4(c)). Also, the prevalent technologies in both collaborative and non-collaborative parts, presented in Figure 2.6 and Figure 2.5, respectively, are present in the scenarios. Those technologies may not require installation such as laser, IMU, compass, or re-used such as Wi-Fi.

2.5.2 Analysis of technologies, techniques, and methods used in CIPSs

2.5.2.1 Non-collaborative part

In accordance with the outcomes of Section 2.4.3, in 66 papers the positioning is performed in a two-step procedure. In the first step, each node/actor estimates its initial position using only its collected data and a position estimation method, which uses one or more technologies [72, 73, 75, 76, 78, 80, 81, 82, 83, 17, 14, 86, 87, 89, 90, 91, 92, 12, 93, 7, 95, 96, 8, 97, 98, 99, 100, 102, 9, 103, 139, 105, 106, 107, 108, 109, 112, 113, 114, 116, 41, 117, 118, 119, 120, 10, 121, 11, 118, 15, 123, 13, 62, 124, 63, 18, 64, 16, 125, 126, 130, 132, 133, 134, 135, 136]. In the second step (collaborative part), the initial estimated position of the raw data is used to enable or enhance the position of other users. The other 18 papers are completely collaborative, as they entirely relied on a collaborative method, named "cooperative methods" in Figure 2.5, to compute the position of the nodes/actor. In short, the systems did not perform stand-alone positioning but directly processed the raw data with the corresponding proposed collaborative method [74, 77, 84, 79, 85, 88, 94, 101, 104, 115, 111, 110, 122, 129, 128, 127, 137, 131].

The most popular methods used in the non-collaborative phase are PDR [130, 41, 117, 120, 10, 118, 112, 116, 106, 107, 109, 99, 95, 96, 87, 89, 90, 91, 86, 81, 133, 134, 135, 136], Ranging [13, 64, 119, 100, 9, 139, 82, 98, 121, 14, 102, 133], RSS-based [18, 10, 118, 15, 112, 8, 92, 7, 78, 73], k-NN [125, 62, 41, 123, 107, 108, 97, 103], fingerprint-based [9, 87, 89, 91, 72, 132, 136, 138] and multilateration [126, 93, 83, 75]. The aforementioned methods are mainly combined with two principal positioning techniques, RSSI, which includes fingerprinting techniques [123, 105, 97, 99, 103], and DR [125, 62, 64, 41, 118, 119, 10, 122, 15, 123, 111, 112, 105, 107, 108, 8, 97, 98, 101, 9, 103, 92, 12, 93, 94, 7, 87, 89, 91, 79, 82, 17, 84, 77, 78, 76, 74, 73, 72]. The first one is based on communications technologies, principally Wi-Fi, and the second on inertial sensors. Both technologies have well-known disadvantages, among which are that Wi-Fi-based systems have positioning accuracy errors of several meters and IMU-based systems could have cumulative drift errors. On the contrary, both might be seen as solutions that do not require infrastructure (infrastructure-less). In reference to the Wi-Fi technology, a regular accuracy of a few meters of error can be achieved, at no extra expense, by reusing the already existing deployed infrastructure designed for communications. Predictably, the majority of collaborative works attempt to leverage frequently used, inexpensive, and straightforward IPSs with known disadvantages to enhance them through collaboration. Even though it is widespread in traditional IPS, in CIPSs, to combine two or more technologies is infrequently in the non-collaborative [89, 87, 91, 107, 112, 41, 10, 118] and in the collaborative [9, 107, 120, 10] parts. It should also be noted that only one article [10] combines multiple technologies in both parts, Wi-Fi and Bluetooth in the collaborative part and Wi-Fi and IMU in the non-collaborative part.

In the non-collaborative phase, there is less use of positioning technologies that need high positioning accuracy, extensive infrastructure, and accurate calibration of the anchors. Some of the probable reasons are: the low probability of finding these technologies embedded in wearable and mobile devices, and tracking hand-held, for example, Wi-Fi and inertial sensors are embedded in mobile devices, but a scarce number of them support UWB; the high implementation expenses of these technologies make it more attractive to explore inexpensive alternatives or without infrastructure; these technologies are no needed for collaborative approaches, due to the deployed infrastructure covers completely the positioning scenario and the positioning technology is sufficiently accurate [52]. Another notable finding in the non-collaborative part is the absence of information about several crucial elements of the CIPSs.

Approximately a 25% of the articles reviewed did not provide sufficient information regarding the positioning methods used, they only group them as fingerprint-based [9, 87, 89, 91, 72, 132, 136, 138], ranging [13, 64, 119, 100, 9, 139, 82, 98, 121, 14, 102, 133] and RSS-based [18, 10, 118, 15, 112, 8, 92, 7, 78, 73] methods.

Regarding the benefits and drawbacks of the five most prevalent non-collaborative methods, in general, the PDR-based methods produce a decent approximation of the trajectory, however, due to cumulative errors, their positioning accuracy decreases over time. Regarding the ranging methods, while NLOS conditions have a detrimental effect on them, under LOS conditions and adequate modeling achieve a more accurate position. RSSI-based methods are simple and easy to implement, nevertheless, the accuracy of the estimated position relies on the stability of the RSSI values obtained. To work, fingerprint-based methods require a top-notch radio map (i.e., a database of previously collected data in the environment). Despite the fact that *k*-NN is a straightforward fingerprint-based method able to provide excellent position accuracy, its computational complexity increases as the data (APs and reference samples) to be processed in the operational phase increases. Table 2.5 presents the advantages and disadvantages of the aforementioned methods.

Table 2.5 Advantages and disadvantages of prevalent non-collaborative methods used in CIPSs. Source [3].

	Method	Advantages	Disadvantages
Non-Collaborative	PDR-based	•Provides reasonable estimate of a walking person's trajectory moving in a steady way	•Suffers from accumulative errors
	Ranging	•Presents good performance on LOS when the signal propagation is well modeled (e.g., VLC technology and Lambertian radiation pattern)	•Relies on radio wave propagation model •Geometry of the scenarios may affect the estimation accuracy •NLOS condition usually degrades the distance estimation
	RSSI-based	•very simple implementation •Low computational cost	•Depends on radio propagation model characterization •Accuracy of the position estimation directly dependent on the RF signal strength quality
	Fingerprint-based	•Uses empirical data for calibration and operation, which might better mimic the real scenario	•Data collection can be very demanding •Radio map's quality degrades if environmental conditions change
	k-NN	•Widely known and very simple implementation •Low computational cost and high accuracy	•Selection of K determines the performance •It is a universal classification/regression model. Therefore, it does not consider the logarithmic nature of the RSS values and the non-linear nature of the signal propagation. •Very demanding if the number of reference samples and the number of APs are both high.

2.5.2.2 Collaborative part

In accordance with the outcomes of Section 2.4.4, the RSSI technique is prevalent and is used with a wide variety of communication technologies. The RSSI is widely used to compute the distance between transmitter and receiver devices. Generally, the range positioning technique is often referred to as RSSI [140, 141, 142]. TWR and ToA/ToF techniques are less common used, and typically they are combined with communications technologies such as UWB, Bluetooth, and Wi-Fi. It should be noted that an adequate combination of technologies, techniques, and methods is necessary for effective CIPSs performance (e.g., position accuracy and precision, robustness, energy consumption, etc.), ensuring that their advantages outweigh their limitations. The best CIPS in terms of accuracy and precision positioning rely on VLC [124] and UWB [104] technologies, which already offer great accuracy and precision in traditional positioning systems.

In around half of the works, to determine the relative distance between users/actors, the collaborative part uses mainly methods based on RSSI (also known as ranging/RSSI ranging). However, for the remaining works, the authors present a particular positioning method for the collaborative part that is not frequently used by other researchers. When analyzing these methods, we notice that each one of them was proposed to fulfill different purposes. For example, the robustness of CIPSs is enhancing through multidimensional scaling, gaussian weight function, and particle filter methods [17, 87, 105, 109]. Despite the high computational cost of belief propagation, it is primarily implemented to provide low position error in CIPSs. So, CIPSs that use these methods focus on providing an adequate balance between position accuracy and computational processing [89, 88, 98, 15, 121, 13, 79, 126]. The power consumption issues in CIPSs have been addressed mainly with the implementation of geometric and trilateration algorithms [9, 10]. To enhance the position precision the LS and EKF methods have been implemented in CIPSs based on UWB technology [16, 104].

Similar to non-collaborative methods, collaborative ones have benefits and drawbacks. The six prevalent collaborative methods are: particle filter [125, 118, 118, 112, 115, 106, 107, 109, 87, 91, 82, 78, 72, 135, 136, 138]; belief propagation [13, 124, 119, 120, 121, 98, 85, 14]; EKF [129, 130, 114, 104, 139, 95, 96]; geometric algorithm [10, 123, 113, 116, 131, 132]; LS [16, 126, 122, 12, 137]; trilateration [8, 9, 7, 83].

One of the key benefits of particle filter-based methods is their capacity to handle non-gaussian and non-linear estimates; nevertheless, as position accuracy increments, so does the computing cost of these methods (increasing the number of particles). Despite the computational complexity of belief propagation-based methods, they are very reliable and adaptable for use with many statistical models. Contrarily, the advantage of the trilateration, geometric algorithms, EKF, and LS is their computational simplicity. EKF method can deal with no-linear problems, however, an optimal estimation can be just achieved under gaussian noise conditions. The accuracy of the position estimated by geometric algorithms is linked to the amount and distribution of nodes in the environment. For example, when they have poorly distributed the accuracy of the estimated position decreases. One of the main disadvantages of LS is that it is only designed to solve linear models. Trilateration methods rely on node collinearity and a number of nodes greater than 2 to work, and its accuracy is highly dependent on the line of sight between nodes.

Table 2.6 presents the advantages and disadvantages of aforementioned methods.

2.5.2.3 Overall concerns

Despite the literature about IPSs reporting numerous cases where diverse technologies are fused to enhance position accuracy and precision, and robustness [143, 144, 145], sensor fusion is uncommon in CIPS. In the non-collaborative part, only seven works ([87, 91, 41, 10, 118, 112, 107]) use sensor fusion, and in the collaborative, just one ([110]). Furthermore, none of CIPSs have presented a scenario considering heterogeneous non-collaborative positioning systems based on diverse methods, techniques, and technologies (e.g., the collaborative scenario in Figure 2.1). Overall, each CIPS provided a collaborative system based on a non-collaborative part, which contains a straightforward positioning approach. In our opinion, device heterogeneity, and hence sensors, should not be overlooked, as real-world situations will involve a variety of heterogeneous data sources. Therefore, the development and implementation of applications that can use as many data sources as possible in their algorithms should be encouraged.

Other advantages of CIPSs found in our review are: CIPSs, through the use of the collaborative users/devices as extra nodes of the infrastructure, have increased

Table 2.6 Advantages and disadvantages of prevalent collaborative methods used in CIPSs. Source [3].

	Method	Advantages	Disadvantages
Collaborative	Particle filter	•Capable of handling non-Gaussian and non-linear estimations •Methodologically simple and flexible •Permits to control the effects of increasing the number of dimensions of the state space •Able to approximate any probability density function in the state space	•Performance degrades considerably as the state-space dimension increases (curse of dimensionality) •Number of particles is a trade-off between computational complexity and accuracy •Issue of filter initialization
	Belief propagation	•High reliability •Works with a wide variety of statistical models •Efficient computing of distribution based on the graphical model •Easy representation of multi-modal distributions	•The computational costs are considerably high
	EKF	•Capable of handling Non-linear models •Low computational complexity	•EKF is designed for Gaussian noises
	Geometric algorithm	•Low computational complexity, due to estimate the position using only the geometry based on the signal parameters	•Accuracy is directly related to the geometric positioning of the nodes
	LS	•Easy to implement •Provides a solution of relatively low complexity	•Works only with linear models
	Trilateration	•Low computational complexity and easy implementation with basic geometry principles	•3 non-collinear points are needed •Requires LOS measurement

coverage area without building an extra costly and sophisticated infrastructure [7, 8, 9]. Also, some CIPSs improved the positioning certainty of users/devices by using belief propagation and the absolute position and relative distance between users computed in the non-collaborative and collaborative parts, respectively [124, 13, 14]. It seems that a critical factor to improve the position is the information/measures provided by the users with LOS conditions.

Almost all the papers reviewed (90.5%) do not approach the communication protocol or device synchronization since they are primarily concerned with proving the viability of the collaborative system rather than dealing with real-world issues. Collection Tree Protocol (CTP) [83] and User Datagram Protocol (UDP) [41] are the unique protocols identified in our review. In some cases (e.g., [62]), the papers refer to D2D communication without mentioning the specific protocol utilized. The predominant device synchronization used reported is TWR [62, 117, 118, 115, 14]. Alternatively, as a more accurate way to determine the time of flight between Bluetooth nodes, hop-synchronization with GNSS time is employed [12].

Several important underlying issues received low attention or none at all. For instance, although optimizing the power consumption of CIPSs may motivate users to use them, only three articles took energy usage into account. [134] presents a method to reduce message re-broadcasting among users and conserve energy. The work in [10] presents a decentralized CIPS and an evaluation of its keys components, concluding that the components that use more energy are the operating system, Wi-Fi and Bluetooth module with 30%, 20%, and 14% of the total device's energy. [9] and [10], concluded that the scanning process of surrounding nodes (e.g., BLE anchors, Wi-Fi APs, etc.) is one the tasks that drain more the energy in CIPS. In [10], researchers reduce power consumption through intermittent node-scanning, however, it also reduces position accuracy.

Security and privacy issues were not covered by the researchers in the CIPSs presented, as they mostly focused on a proof-of-concept to demonstrate increased accuracy. However, CIPS are specifically at risk since careless data transmission during cooperation, such as the transmission of unencrypted data, may allow than third-party determines the user location.

2.5.3 Evaluation of CIPSs

The design and planning of the experiments are one of the main aspects to consider in the evaluation of CIPSs. Although experimental evaluations are preferred, and from 2018 to 2020 there was a significant increase of them (outnumbering simulation-based evaluations), in general, we still notice that the percentage of simulation-based evaluations (45.24%) exceeds the experimental ones (41.67%). The experimental evaluations allow evaluating in greater detail the operating conditions of the systems under conditions intrinsic to real-world scenarios [62, 10]. However, they present drawbacks such as: complexity in their configuration and implementation [41, 118], time-consuming [11, 120, 106], susceptible to diverse kind of failure and errors [10, 118], and (potentially) costly [118, 114, 104]. Also, experimental evaluations face issues related to real-world conditions, which are no easy to control or avoid, such as accuracy degradation due to NLOS conditions [10] and signal attenuation/interference [10, 110].

Simulation-based evaluations allow us to simulate data and collaborative algorithms in well-controlled environments, avoiding problems caused by hardware failure. Additionally, simulations give researchers the versatility to execute an experiment multiple times with diverse setups. For instance, in diverse execution of an experiment, we can set the granularity of samples and references [13, 119], the configuration of virtual hardware used [122, 115, 88], the conditions of the environment (e.g., NLOS and LOS areas) [13, 18], and the dimension of the collaborative users/nodes network used [119]. Only a small percentage of papers (8.33%) uses both evaluations: simulations to evaluate in more challenging environments while the experimental ones are used for simpler testing in real scenarios for system validation.

With respect to the metrics, from Figure 2.4(d), we can notice that all papers of the review include positioning accuracy. In detail, we see that this metric has been measured in different ways. We list them in descending order by popularity as follows: the Cumulative Distribution Function (CDF) error [62, 63, 123, 118, 10, 120, 11, 115, 105, 107, 108, 97, 101, 102, 139]; Root Mean Square Error (RMSE) [124, 18, 16, 15, 111, 115, 98, 110]; standard deviation of the error [63, 41, 8, 99, 9, 7]; minimum mean square error [13, 119, 122, 118, 106]; and finally the average positioning error [121, 123, 112, 94]. Because of this variety, a comparison of position accuracy between proposed systems is unviable.

In terms of computational complexity, the systems evaluate it regarding factors such as processing duration to determine/estimate the position [13, 121], the computational load required by the CIPS to determine/estimate the position [13, 18, 119, 111], and the data traffic [98]. Within the suggested solutions proposed to minimize the computational complexity, we have: to decrease the computational and communication/data load by implementing an analytical approximation with a belief propagation scheme to process the device-to-device data [119, 98]; to decrease the processing duration through the reduction of the size of the users' set that the collaborative algorithm considers in the execution [13, 121]; to decrease the workload by simplifying the non-convex models, used to model the positioning problem, using a quasi-convex model [18].

The robustness of the positioning system defines how stable the system is against disturbances against failures and/or disturbances. Robustness was addressed by few CIPSs [87, 109, 105, 14, 17]. The approaches that face robustness issues aim to protect the systems against inadequate ranging estimation, node failures, few positioning data, and outdated radio maps. Within the relevant suggested solutions, we have: to guarantee robustness against node failure by using sum-product methods in the wireless networks [14]; to prevent instability of position estimates due to noisy and scarce positioning raw data by implementing procrustes analysis and multidimensional scaling algorithms [105], and to reduce the impact of multi-path by using a gaussian neighborhood weighting method [17].

Position precision [104, 16] and energy consumption [10, 9, 133] (discussed in Section 2.5.2.3) are the two least used evaluation metrics. They have only lately been taken into account and both rely on UWB.

2.5.4 Recommendations, gaps, and limitations

Considering the findings and the information extracted from the articles included in our CIPS systematic review, we draw the following recommendations:

1. Architecture: In CIPSs, the decentralized architecture prevents issues related to high-volume data transfer, such as delay in the data transmission/reception, and saturation of communication channels, which are common in centralized architectures. So, due to its advantages, the decentralized architecture is the alternative most adequate for CIPSs. Nevertheless, from the view of computational performance, the heterogeneity of devices might limit the implementation of complex algorithms or cause a not homogeneous execution in collaborative devices.
2. Infrastructure: Infrastructure-less or signals of opportunity-based approaches are preferred in CIPS, mainly because they provide versatility to the systems to be used in diverse scenarios (i.e., users moving from a scenario to another) and indoor environments applications, and their zero-cost infrastructure to cover the operational area. Nevertheless, using an infrastructure-less approach instead of an ad-hoc infrastructure for the CIPS creates design challenges such as compensating for inaccuracies in position estimation caused by uncontrolled scenarios. An infrastructure-based approach may be beneficial only in certain real-world scenarios.
3. Technologies: Although BLE and Wi-Fi technologies are not among the technologies that provide the best position accuracy (namely, high-accuracy posi-

tioning technologies are VLC, UWB, and 5G), they are the best option for collaborative systems. Additional to high accuracy and precision positioning, others important requirements are the availability of the technology in the devices and environments, cheap deployment, and low power consumption. As is well-known, BLE and Wi-Fi fulfill these requirements. Changes in the supporting hardware and broad availability, such as those brought on by 5G, might lead to a change in preferred technology.

4. Techniques: Focusing on the accuracy performance of CIPSs and one of the most suitable technologies (i.e., Wi-Fi), we can consider that fingerprinting is one of the most suitable techniques. Unlike other techniques, fingerprinting does not require knowing the location of the anchors (e.g., APs) to estimate the position. On the one hand, techniques such as RSSI coupled with ranging/distance-based methods provide a better position accuracy than fingerprinting due to the location of the reference anchors considered in the estimation methods. On the other hand, knowing the location of the reference anchors is not an automatic task, which is one of the limitations of the RSSI technique coupled with those methods.
5. Methods: It is challenging to define which method is the most suitable because the systems have been tested under a variety of scenarios and conditions. So, in the design of CIPSs, diverse methods should be tested under operational conditions and the method to be selected is the one that provides the best result depending on the performance to be optimized (for example, position accuracy, robustness, etc.).

The aforementioned recommendations provide hints in the design of CIPSs. However, due to the broad range of solutions reported, the selection of the technology, techniques, and methods, must be done following the design requirements of the CIPS to be designed.

As a result of the analysis performed in our systematic review, we identified some limitations, gaps, and future research avenues, which are described as follows:

- The studied collaborative systems concentrate on enhancing just one key aspect (e.g., position accuracy, robustness, power consumption, etc.). However, a trade-off between the different aspects is missing, which is the principal limitation identified in CIPSs.

- Overall, heterogeneous positioning solutions, that involve multiple technologies, techniques, and methods in each of the collaborating devices, are not used in the collaborative systems included in the review. Also, sensor fusion was not used by the CIPS reviewed. We consider that, as has been shown in traditional IPS, technology variety in both parts, non-collaborative and collaborative, may provide additional robustness to the CIPS.
- The users' privacy and security of the CIPSs were not taken into account in the evaluated papers. Privacy is one of the major issues in systems that involve the exchange of data. The CIPSs use communication technologies to exchange information between devices. So, they are prone to be attacked and modify the positioning data transmitted, and put at risk the users and their privacy. Also understudied is power consumption, a key overall concern that may dissuade people to install CIPS applications on their devices to help neighbouring users.
- The non-collaborative technology used in CIPS is the main influence in selecting the type of evaluation used in CIPS. There is no impartial evaluation methodology that can evaluate the non-collaborative technology used in CIPS independently of the kind of non-collaborative technology used. Comparable evaluation metrics are a key component of such a methodology. Additionally, evaluation methodologies, which consider various technologies operating at once has not yet been proposed.
- Approximately half of the examined works use simulations to avoid the expensive hardware deployment and intensive physical labor needed in the experimental evaluation. Despite the fact that advanced simulation algorithms can reproduce conditions presented in real scenarios, experimental tests to validate the performance of CIPSs under real scenarios are still needed. Therefore, providing databases containing positioning data involving various users and sensors could be beneficial for the reproducibility, repeatability, and evaluation of CIPSs and also to motivate the development of more CIPSs.

2.6 Systematic review update

The systematic review presented above was carried out in the early stages of this Phd research, in order to provide us with the state-of-the-art related to CIPS at that moment (beginning of 2021), and to analyze and evaluate them. For completeness of this PhD dissertation, and to expand the systematic review's usefulness and the results presented, we updated it considering the articles published between 2020 and 2022. We used the same methodology as explained in Section 2.3, restricting the search to documents published between 2020 and 2022. Even though 7 articles from 2020 were included in the original systematic review, we included missing articles in the update. The database queries for the original review were made on January 8$^{\text{th}}$ 2021, and at that time, not all 2020 records were included in the databases.

As a result of the selection process, 15 additional articles were selected for thorough analysis and inclusion in the systematic review update: 5 more articles in 2020 [146, 147, 148, 149, 150], 3 in 2021 [151, 152, 153] and 7 in 2022 [154, 155, 156, 157, 158, 159, 160]. Adding the articles from 2020 included in the original systematic review (7 articles) with those included in the update of the same year (5 articles), we arrive to a total of 12 articles in 2020, 2 less than in 2019. In addition, in 2021, the number of articles decreased drastically (only 3 articles), and in 2022 the number of articles started to increase again. It should be noted that the number of publications between 2020 and 2022 must be carefully interpreted: firstly, the COVID-19 pandemic and lock-downs affected the research activities, such as attendance at laboratories or workplaces and on-site experimentation; secondly, international forums and congresses related to positioning, localization and navigation were re-scheduled for 2021 or canceled; thirdly, some research groups working on positioning and LBS reoriented their research to health-related topics (e.g., contact tracing, mobility analysis) to contribute to facing the pandemic situation. The above circumstances dropped the projected number of publications and experiments for 2020-2022. So, the years 2020, 2021, and 2022 are atypical in terms of publications, and they cannot be considered representative in terms of the overall evolution of articles. Figure 2.7 presents the distribution of the articles published regarding CIPS between 2020 to 2022 and the results of the analyzed dimensions (i.e., evaluation metric (Figure 2.7(**a**)), system's architecture (Figure 2.7(**b**)), system's infrastructure (Figure 2.7(**c**)) and system's evaluation (Figure 2.7(**d**)). Additionally, the percentage of each dimension is shown in the pie charts.

Regarding the evaluation metric used in the 15 new articles selected, we found that the position accuracy was evaluated in all the articles, and the computational complexity together with position accuracy only in 2 articles [154, 155].

With respect to the architecture, listed in descending order by the number of arti-

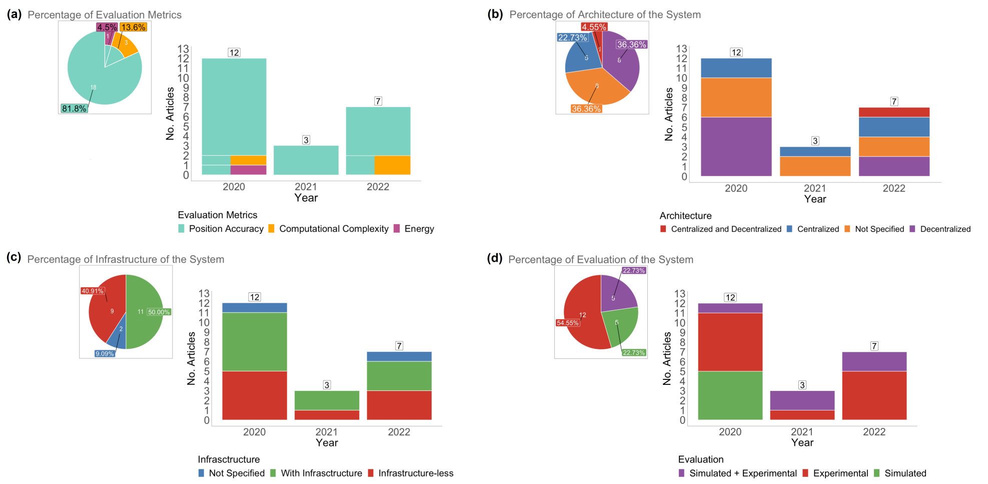


Figure 2.7 Updated distribution of CIPSs over time (**a**) Evaluation metrics. (**b**) Systems' architecture. (**c**) Systems' infrastructure. (**d**) Systems' evaluation.

cles, we found that 7 articles [154, 158, 152, 153, 146, 150, 148] did not specify the architecture used, 4 [156, 160, 151, 147] used centralized architecture, 3 [155, 159, 149] a decentralized architecture, and 1 [157] can be used with both architectures.

The use of supporting infrastructure in CIPS was the most predominant with 9 systems [154, 155, 160, 152, 153, 146, 147, 149, 150], in second place, the infrastructure-less with 4 systems [156, 158, 159, 151], and in third place, 2 systems [157, 148] for which the infrastructure used was not specified.

Regarding the evaluation of the systems, 8 [154, 156, 157, 159, 160, 151, 149, 150] of them were evaluated experimentally, 4 [155, 158, 152, 153] were evaluated using both experimental and simulated evaluations, and 3 [146, 147, 148] through only simulation.

In the non-collaborative part of the systems, the most used technologies are Wi-Fi [155, 156, 151, 147], UWB [154, 157, 149, 150] and IMU [158, 159, 160, 147] used in 4 systems each, followed by Bluetooth [160, 153, 147] and other technologies RF [152, 146, 148] used in 3 systems each, and the least used are 5G [153], and camera [154] used in 1 system each. Regarding techniques, the most predominant is RSSI used in 6 systems [155, 160, 152, 146, 147, 148], followed by DR used in 3 [158, 159, 160], fingerprinting [156, 151] and TWR [154, 149] used in 2 systems each, and AoA [153] used in 1 system. Considering the methods, the most used are fully cooperative methods used in 6 systems [156, 157, 153, 146, 147, 149], followed by ranging used in 4 [154, 155, 152, 148], PDR-based used in 3 [158, 159, 160], and trilateration [160, 150] used in 2 and k-NN [151] used in 1 system.

In the collaborative part of the systems, the Wi-Fi [155, 156, 151, 147], Bluetooth [159, 160, 153, 147], UWB [154, 157, 149, 150] and other RF technologies [158, 152, 146, 148] are used in 4 systems each, so there is no winning technology. Regarding techniques, the most predominant is RSSI used in 6 systems [155, 160, 153, 146, 147, 148], followed by position sharing [157, 158, 159] and TWR [154, 149, 150] used in 3 systems each, fingerprint used in 2 [156, 151], and ToA used in 1 system [152]. Considering the methods, the predominant methods are multidimensional scaling [154, 156], belief propagation [157, 149], and factor graph [152, 153], which are used in 2 systems each, and the least used are bezier curve [158], geometric algorithm [160], EKF [150], semidefinite programing [155], fisher information matrix [146], Deep Neural Network (DNN) [147], bayesian filtering [159], gaussian process [147], and RSS difference [148] in 1 system each.

The results of the analysis of the articles included in the update of the systematic review verified the correctness of the trends and proportions of the dimensions (e.g., technologies, techniques, methods, etc.) analyzed and reported in the systematic review (2006-2020). Within the findings, regarding evaluation metrics, we can observe from the pie chart (Figure 2.7(**a**)) that the prevalent metric is position accuracy (100% of papers), followed by computational complexity evaluation together with position accuracy (13.6%). In terms of the system's architecture, the pie chart of Figure 2.7(**b**)) shows that decentralized is the most popular (36.36%). The only exception with respect to the previous trends reported is the infrastructure used in CIPSs. In the last 3 years, based on the pie chart of Figure 2.7(**c**), infrastructure-based (50%) exceeds around 9% the percentage of the infrastructure-less (40.91%). However, considering all the years (2006-2022), the trend of systems that do not use infrastructure has not changed. In terms of the system's evaluation, the pie chart of Figure 2.7(**d**) shows that the experimental evaluations are prevalent (54.55%) maintaining the trend reported in the previous systematic review.

Additionally, among the new results, we identified the use of new methods in the collaborative part, such as factor graph, bezier curve, fisher information matrix, DNN, gaussian process, and RSS differences. Also, we can highlight that two articles focused on two aspects not previously addressed in depth, privacy was dealt with in [147]) while an incentive mechanism for CIPS was proposed in [146]. Regarding privacy, the authors proposed a framework based on federated learning, DNN and the gaussian process to compute the position, and the parameters are encrypted using homomorphic encryption. With respect to the incentive mechanism, the authors proposed an economic-based mechanism to incentivize users to collaborate through a game-theoretic algorithm for budget decisions, where the users/devices set a price to buy data from other users/devices.

To sum up, the supplementary analysis confirms that the trends and conclusions in technologies, techniques, methods, evaluation metrics, architecture, and evaluation are aligned with those reported in the previous systematic review (2006 to 2021). The only difference corresponds to the CIPSs infrastructure used. In this new analysis, the predominant infrastructure is infrastructure-based. Nevertheless, this change does not affect the overall trend (2006 to 2022), which indicates a principal use of infrastructure-free. Moreover, we identified an incipient interest in the study of privacy in CIPSs.

2.7 Chapter summary and discussion

In this chapter, we presented a systematic review and its update focusing on CIPSs. As a result of the systematic process, 84 significant papers from 2006 to 2020 (systematic review) and 15 additional articles from 2020 to 2022 (systematic review update), respectively, were identified and grouped considering the following aspects: evaluation metrics, infrastructure, technologies, techniques, methods, and architecture. The analysis carried out showed that there has been an overall increase in the number of papers over the years, indicating a rising interest in the study of the CIPSs among scientists.

Our analysis demonstrates the widespread use of decentralized architectures, particularly in the past five years. On the one hand, decentralized architecture is preferred due to the computational load is divided among all the collaborative devices, and the data shared mainly is preprocessed data, which reduces the transmission load and avoids the overload of communication channels. Contrarily, the reported drawbacks of a centralized architecture include delay in the data transmission/reception, scalability, saturation of communication channels, lack of robustness against failure, and computational workload due to high-volume data transfer and processing. Also, we found that infrastructure-less systems are widely used, probably due to practical rather than technical considerations. These considerations include the utilization of readily available hardware and generally cheaper costs, which allows the operation of the positioning systems in real-life scenarios (e.g., universities, offices, libraries, etc.). It should be noticed that, although deploying ad-hoc infrastructure for positioning is a more expensive and exhausting activity, the approaches based on it may produce results that are more accurate than infrastructure-less approaches.

We analyze the technologies, techniques, and methods in CIPSs considering independently its collaborative and the non-collaborative part. In the non-collaborative part, each device/node collects the raw data and independently computes its position. The findings reveal a broad variety of technologies, methodologies, and procedures, making it challenging to identify a successful combination. The popular coupled technology and technique, used in the non-collaborative part, are: IMU with DR, and Wi-Fi with RSSI and fingerprinting. The use of the aforementioned combinations is recommended in mobile device-based positioning systems and under scenarios with a limited budget to implement the positioning infrastructure.

On the other hand, in the collaborative part, where relevant data is exchanged and the user's position is estimated based on it, researchers prefer RSSI based on Bluetooth and Wi-Fi technologies. These technologies are widely available, completely infrastructure-less, energy efficient, and inexpensive. With respect to methods, due to each of them having different goals, none of them stands out.

Some CIPS are completely collaborative. In those cases, the non-collaborative part is only devoted to collecting data, which will later be processed by the collaborative method. We recommended decentralized systems in which the collaborative and non-collaborative parts can work separately to estimate the user's position. In centralized systems, the central node is a critical part and the positions cannot be estimated if it fails.

Until now, the majority of CIPSs evaluations have used simulations. Nevertheless, in the last years, experimental evaluations noticeable increased, therefore, it is likely that in the coming years, we may be facing a change in trend. The complicated real-world situations are considerably better mimicked by empirical evaluation, and the resulting findings are more valuable to the community. Nevertheless, obtaining the necessary results requires considerable labor and, occasionally, the deployment of pricey technology. We consider that creating databases containing positioning data involving various users, sensors and scenarios could be beneficial for the reproducibility, repeatability, and evaluation of CIPSs. Also, to motivate the development of more CIPSs.

CIPSs presents various advantages against traditional IPSs. CIPSs, through the use of the collaborative users/devices as extra nodes of the infrastructure, may increase the positioning coverage area, which allows positioning users outside of the covered area. In addition, they improve the positioning accuracy of the group of users, by considering in their algorithm the information of neighboring users and using them to extend the number of anchor references. Nevertheless, CIPSs have drawbacks, including long calculation times, heavy node-level computations, and energy consumption. Accordingly, the principal challenge is to reach the trade-off between energy efficiency and other performances such as computational workload, positioning accuracy, and real-time constraints.

We consider that much work remains to be done to improve CIPSs in each of the dimensions identified in our review. For example, the implementation of sensor fusion in both parts of CIPSs (collaborative and non-collaborative); construction of advertising databases that consider heterogeneous devices and collaborative scenarios for the testing and validation of collaborative approaches; inclusion of heterogeneous positioning systems in collaborative devices; inclusion of heterogeneous devices in CIPSs, and implementation of security and privacy in communication protocols.

Based on the information, challenges, and gaps presented in this systematic review, in the next chapters, we fill some gaps and challenges identified. Specifically, we create a mobile device-based BLE database for testing and validating ranging CIPS, considering bidirectional and simultaneous transmission/reception between heterogeneous devices and two real-world scenarios (office and lobby) due that there are no publicity databases available; we propose a versatile and straightforward CIPS baseline scheme designed for developing CIPSs. Based on the CIPS scheme, we developed two variants of a mobile device-based CIPS based on Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs) models, which are evaluated experimentally rather than through simulations. In the CIPSs design, we considered the most important aspects identified in our systematic review, namely the concept of compatibility among CIPS, system modularity, architecture (decentralized), and infrastructure (able to work as infrastructure-based and infrastructure-free). Also, our proposed CIPSs considered the use of different technologies (i.e., Wi-Fi and BLE), methods (i.e., lateration and fingerprinting-*k*-NN), and heterogeneous mobile devices.

3 DATABASES AND SCENARIOS FOR COLLABORATIVE AND NON-COLLABORATIVE INDOOR POSITIONING APPROACHES

The Bluetooth Low Energy (BLE) beacon technology is widely deployed as a part of indoor positioning infrastructure. However, in the research community, there is a growing interest in developing straightforward and inexpensive ranging positioning systems (i.e., infrastructure-less systems) and improving location accuracy in Non-line-of-sight (NLOS) environments. These objectives have accelerated the research in Indoor Positioning Systems (IPSs) based on wearables and collaboration among devices/users. Unfortunately, obtaining the necessary experimental data to enable such systems is very time and resource-demanding, as it requires simultaneously capturing data from the various collaborating mobile devices.

As far as we know, no such empirical datasets existed in the literature before we collected ours. This chapter has four aims:

- firstly, to present a BLE database based on mobile devices, which act simultaneously as transmitters and receivers, for ranging-based collaborative indoor positioning;
- second, to detail the methodology used for the data gathering phase, raw data processing, and the structure of the database;
- third, to technically validate the usefulness of the database through an example (lateration approach based on collaborative users), and
- fourth, to describe the two indoor scenarios where we have collected our datasets for plain fingerprinting, lateration, and ranging collaborative indoor positioning in the aforementioned scenarios.

The information about the datasets and indoor scenarios provided in this chapter were used to evaluate and analyze the approaches proposed in Chapter 4 and

Chapter 5.

The scenarios and databases presented in this section were used as follows:

- The office scenario together with the BLE database for range estimation in collaborative indoor scenarios (Subset-C) presented in Sections 3.2.2 & 3.2.4, respectively, were used to experimentally evaluate and validate the collaborative approach presented in Section 5.2 and in [22].
- The office scenario together with the BLE database for range estimation in collaborative indoor scenarios (Subset-A) presented in Sections 3.2.2 & 3.2.3, respectively, were used to experimentally evaluate the Logarithmic Distance Path Loss (LDPL) model presented in Section 4.1.1 and in [21]. Furthermore, the office scenario and Subset-A were used as a basis for testing the Received Signal Strength Indicator (RSSI)-fuzzy classifier presented in Section 4.1.2 and in [4].
- The new scenario (lobby scenario) together with the extended ranging collaborative dataset and the BLE and IEEE 802.11 Wireless LAN (Wi-Fi) radio maps presented in Sections 3.5.1, 3.5.2 & 3.5.3, respectively, were used to experimentally evaluate and validate the collaborative approach presented in Section 5.3.
- The first BLE radio map presented in Section 3.5.3.1 was used to experimentally evaluate and validate the collaborative approach presented in Section 5.3.
- The second BLE radio map presented in Section 3.5.3.1 was used to experimentally evaluate and validate the lateration BLE–RSSI method based on combinatorial BLE anchor selection presented in Section 4.2.1 and in [6].
- The Wi-Fi radio map presented in Section 3.5.3.2 was used to experimentally evaluate and validate the collaborative approach presented in Section 5.3. Moreover, the Wi-Fi radio map, was used to experimentally evaluate the fingerprinting-based positioning system presented in Section 4.2.3.

3.1 BLE database for range estimation in collaborative indoor scenarios

In the last few years, the technological advancement of wearable devices and the rising demand for infrastructure-independent positioning systems have accelerated the development of wearable-based positioning systems for Location-based Services (LBS) applications. In spite of the variety of indoor positioning technologies available, BLE is extensively utilized because it is already built into mobile devices, is inexpensive, has low power consumption, and provides both positioning and communication capabilities. Indeed, BLE is an easy-to-use technology for implementing IPS based on RSSI [161, 162, 163, 164, 165]. For example, IPSs based on iBeacon protocol [166, 167, 165] allow mobile devices to transmit and receive information using the BLE packets, in a short distance, between them [167]. In recent years, BLE has proven its usefulness and importance in real-world applications, such as the COVID-19 contact-tracing apps [168].

Nevertheless, the propagation of radio frequency signals, including BLE, is prone to signal attenuation, interference, and multi-path propagation [169, 168], especially in harsh environments under complex geometries, NLOS conditions, and the presence of crowds. These events cause a random variation in the RSSI, resulting in a fluctuation in the position estimate [168]. RSSI-based positioning – such as proximity, ranging and fingerprinting – is the most affected by these adverse conditions [164].

Nowadays, the ubiquity of mobile devices and the increasing density of mobile device users within small indoor environments (e.g., offices, libraries, and classrooms) has been exploited to design Collaborative Indoor Positioning Systems (CIPSs) and/or enhance distance estimation between users. CIPSs, as explained in Section 2.2, estimate/improve the neighboring users' position based on exchanging absolute positions and measuring the relative distance between neighboring devices [170]. Figure 3.1 exemplifies a CIPS integrated by six smartphones, where the Line-of-sight (LOS) between anchors references (Ref.1-3) and User 6 is obstructed by bookshelves causing a poor position accuracy, so, the neighboring users (1-5) collaboratively broadcast BLE information to improve the position of user 6. Nonetheless, in order to guarantee accuracy and robustness of the estimated position based on collaborative approaches, it is fundamental to analyze and study the RSSI under several conditions and environments, and involve diverse devices. On the other side, thanks to its implementation in indoor contact-tracing apps, research for distance estimation (i.e., proximity) applications, primarily based on BLE, has been boosted during the COVID-19 pandemic. However, similar problems as those of IPSs are noticed, mainly a high number of false positives caused by diverse factors related to the indoor environment, such as signal interference between devices, NLOS conditions, and fluctuation in the signal transmission patterns [171].

Figure 3.1 Example of a mobile-device CIPS scenario. Source [21].

Although the new positioning and range approaches have been extensively evaluated mathematically and using simulations, the experimental evaluation with real data (i.e., data collected from diverse real scenarios, devices, and conditions) is primordial to comprehend their behavior under real conditions. Nevertheless, such data collections are time and resource demanding and the generalization of results can be compromised if the data collection performed is limited to the own researchers' facilities. So, sharing databases, including a detailed and systematic methodology of data collection and usage documentation, is a good research practice. Additionally, this practice provides invaluable contributions to the research community, as in many cases, researchers are not able to collect their own data. Using our database, they can still test and validate their solutions using real data collected under diverse contexts and scenarios. Finally, public databases promote the reproducibility of research.

As far as we know, the availability of public databases based on BLE and RSSI, which uniquely rely on mobile devices, in both transmission and reception, is almost nil [161]. In the few that exist, the transmission/reception among multiple mobile devices is not considered. An ample amount of databases are based on fingerprinting systems, considering deployed anchors, off-the-shelf BLE beacons, or other ad-hoc devices, only as transmitters. The receivers, on the other hand, are typically smartphones or other wearable devices [172, 173, 164].

The BLE database for range estimation in collaborative positioning scenarios based on mobile devices is divided into three data collection subsets. The first subset is dedicated to the calibration of parameters used for position estimation in the indoor environment. The second subset is dedicated to ranging and collaborative positioning considering NLOS conditions. The third subset is dedicated to ranging and collaborative positioning considering real office conditions. In the scenarios, the LOS conditions are considered as the direct line-of-sight between two devices with no obstructions in between.

The main description for the three subsets is provided below:

- **Subset-A "Calibration in Line-of-sight (LOS)":** Data necessary for calibrating the parameters used for distance estimation, based on RSSI measurements in LOS, of six diverse mobile devices (five smartphones and one tablet) considering one indoor scenario. RSSI values are measured considering 12 reference points spaced every meter in a straight line.
- **Subset-B "Ranging and Collaborative positioning with NLOS, due to intentional and recurrent walking in the environment":** Data for ranging and collaborative positioning from five motionless mobile devices (also used in Subset-A) in four set-ups with recurrent and intentional walks of one person throughout the indoor scenario, inducing diverse conditions of NLOS.
- **Subset-C "Ranging and Collaborative positioning in real office conditions":** Data for ranging and collaborative positioning from five motionless mobile devices in seven set-ups in normal office conditions (i.e., employees sitting at their desks and periodically strolling around the environment conducting regular office duties).

3.2 Methodology

3.2.1 Hardware and software for BLE advertising and data collection procedure

The data collection and the BLE advertising in the experiments has been performed using six mobile devices. Table 3.1 enlists the mobile devices, sorted by ID number, and details the name, model, brand, and version of the Bluetooth, android, and API of each.

Regarding the software used, the experiments were carried out based on a modified version of the Android application *GetSensorData* [174, 175]. The application was initially designed to collect data from smartphone wireless communications and

Table 3.1 Description of mobile devices. Source [21].

ID	Mobile name	Model	Brand	Bluetooth version	Android version	API version
01	Galaxy S8	SM-G950F	Samsung	5	9	28
02	Lenovo Yoga Book	Lenovo YB1-X90F	Lenovo	4.0	6.0.1	23
03	Galaxy A7 Duos	SM-A7100	Samsung	4.1	7.1.1	25
04	Galaxy S6	SM-G920F	Samsung	4.1	7	24
05	Honor 20 Lite	HRY-LX1T	Huawei	4.2	9	28
06	Galaxy A5	SM-A500FU	Samsung	4.0	6.0.1	23

sensors and save it to *logfiles*, which are text files (TXT extension) with the comma-separated format. However, the BLE advertise mode feature was not included in the original version. Hence, we added the BLE advertise mode feature to the *GetSensorData* application allowing the smartphones to broadcast advertisements via Apple's iBeacon protocol, which is one of the most widely implemented on mobile devices. The iBeacon protocol, through BLE packets, allows to broadcast and receive information between mobile devices within a short range [167]. The broadcasting period of the iBeaconBLE packets was set to 100 ms (i.e., 10 Hz). Then, on each of the smartphones, the modified version was installed. Although BLE has been supported from Android version 4.3, the transmission of BLE beacons has only been possible since Android version 5.0 (LOLLIPOP) with API 21 [176]. The application is available at the GitLab repository [177].

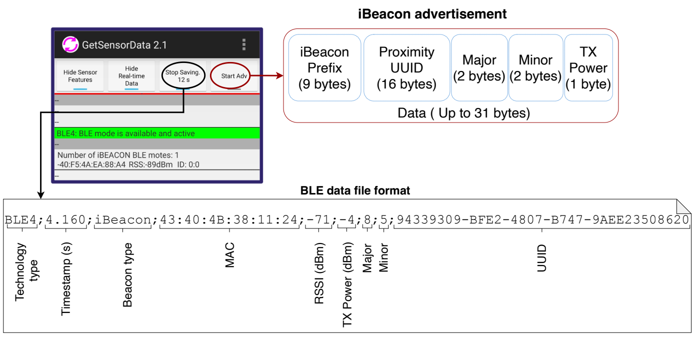


Figure 3.2 User interface of GetSensorData. Source [21].

The User Interface (UI) of the modified version of *GetSensorData* application installed on the smartphones is shown in Figure 3.2. The save sensor data and advertise BLE beacons buttons are on the upper right corner of the UI. The save sensor data button circled in black, allows us to save the information of the received BLE packets, the information of other wireless communications and device's sensors (e.g., Wi-Fi, GNSS, inertial sensor, among others). For example, in our specific case (BLE), the BLE data file format includes the type of technology used (BLE), recorded data timestamp, Beacon type (iBeacon), Media Access Control (MAC), RSSI value measured, TX power, and the identifiers Major, Minor and Universally Unique IDentifier (UUID). The broadcasting of BLE packets is initialized by pressing the advertise BLE beacons button (circled in red). The structure of iBeacon advertisement packets comprises five elements, the iBeacon prefix (9 bytes), Proximity UUID (16 bytes), Major (2 bytes), Minor (2 bytes), and TX power (1 byte) as is illustrated in Figure 3.2. The TX power value of each device corresponds to the average of the RSSI values measured at 1 meter and in LOS from the transmitting mobile. The UUID, Major, and Minor are device identifiers, which allow us to identify and classify with different levels of abstraction, within a network infrastructure, the devices that are broadcasting. For instance, we could use the UUID to group devices installed in a specific building, Major to group them by floor, and Minor to identify each device within the floor. In addition, the receiver adds a sixth element (RSSI), which contains the value of the strength of the received signal measured in dBm. Table 3.2 details the configuration data for the mobile devices used in the data collection procedure. To avoid interference with radio frequency signals, each

Table 3.2 iBeacon identifiers of each mobile device. Source [21].

ID	Mobile name	UUID	Major	Minor
01	Galaxy S8	94339309-BFE2-4807-B747-9AEE23508620	8	1
02	Lenovo Yoga Book	94339309-BFE2-4807-B747-9AEE23508620	8	2
03	Galaxy A7 Duos	94339309-BFE2-4807-B747-9AEE23508620	8	3
04	Galaxy S6	94339309-BFE2-4807-B747-9AEE23508620	8	4
05	Honor 20 Lite	94339309-BFE2-4807-B747-9AEE23508620	8	5
06	Galaxy A5	94339309-BFE2-4807-B747-9AEE23508620	8	6

mobile device used in the experiments was mounted on its own pole at $1.5\,\mathrm{m}$ from the ground in portrait orientation (see Figure 3.3(**a**)).

3.2.2 Data collection scenario

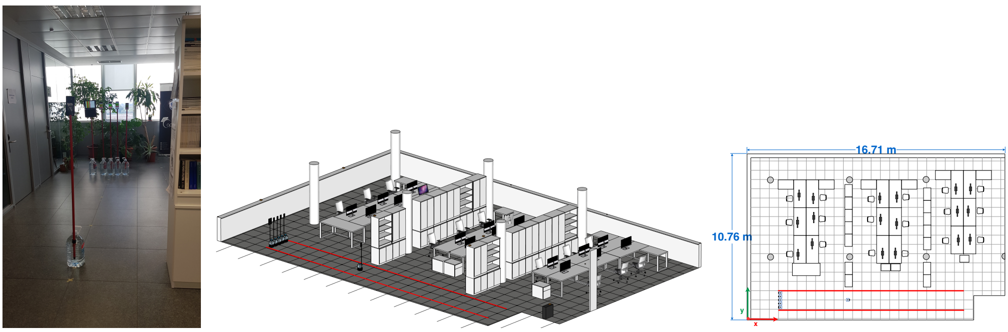
The experiments for the data collection of the three subsets (Subset-A, Subset-B, and Subset-C) were performed in the GEOTEC group's office based at University Jaume I (Castellón, Spain).

Figure 3.1 and Figure 3.3 illustrate the office. The approximate area of the office is 10.76 m by 16.71 m. 14 bookshelves, 7 concrete columns, and three office work areas with desks, chairs, and computers make up the majority of the office. This site has previously been utilized for indoor positioning with Wi-Fi fingerprinting, magnetic fields, conventional BLE, and even sensor fusion [178, 172, 179].

3.2.3 Configuration for the Subset-A data collection

The aim of the data collection of Subset-A is to analyze the BLE signal behavior and calibrate the mobile devices in completely Line-of-sight (LOS) conditions in an indoor environment, i.e., the office scenario described above.

The red lines marked on Figure 3.3(b) and Figure 3.3(c) bound the area (main corridor) used for empirical Subset-A data collection. On the floor of the main corridor, 12 reference points every 1 m in a straight line and in LOS were set, considering the initial point at 0 m and the last point at 11 m. Hence, the attenuation of the RSSI can be measured at each reference point and, for example, be used for tuning propagation models or calibrating the parameters of relative distance estimators.



(a) Real representation **(b)** 3D model **(c)** 2D model

Figure 3.3 Example of the setup for the Subset-A with the distribution of the emitters and received in the office. Source [21].

On the initial point (0 m), we set five of the six devices, listed in Table 3.1, horizontally aligned, that act as transmitters. The unused device, which acts as the receiver, was consecutively set at the reference points located at 1 m to 11 m. To allow each device to act as a receiver, the above procedure was done six times. An example case, where the transmitter devices are horizontally aligned in the initial position (0 m) and the receiver is at 4 m, is illustrated in Figure 3.3(a).

Each receiver mobile device recorded 90 s of raw data (BLE iBeacon and all phone sensors and communications data) at each reference location using the *GetSensors-Data*, and saved it in a *logfile*. 66 *logfiles*, one for each transmitter and reference point was generated. In total, because each of the 66 *logfiles* contains data from 5 separate transmitters, 330 ranging transmitter-to-receiver pairs of 90 seconds were saved. Furthermore, we ensured that the devices' batteries were not less than 80 % of their capacity during the measurements, and, we stayed away from the devices, always retreating to the same location.

3.2.4 Configurations for the Subset-B and Subset-C data collection

For the data collection of Subset-B and Subset-C, we used five mobile devices considering diverse set-ups. Contrary to Subset-A, designed for BLE calibration, Subset-B and Subset-C are designed to test the feasibility of ranging and collaborative positioning using mobile devices and realistic situations.

To this aim, we implemented various device arrangements considering five devices. Also, in order to create NLOS cases among devices, diverse approaches were implemented. As a result, we offer a wider variety and complexity of test conditions reflecting real-life situations for ranging and collaborative positioning approaches. We included the alteration of the number of occupants in the office, the frequency with which people walk and obstruct the LOS between devices, and the use of various fixed obstacles among these approaches. In each setup, each mobile device simultaneously advertises its own BLE messages while reading/saving the RSSI of the received advertisement emitted by surrounding devices (i.e., the other four mobile devices). The ground truth of the mobile devices in each configuration is presented in Table 3.4.

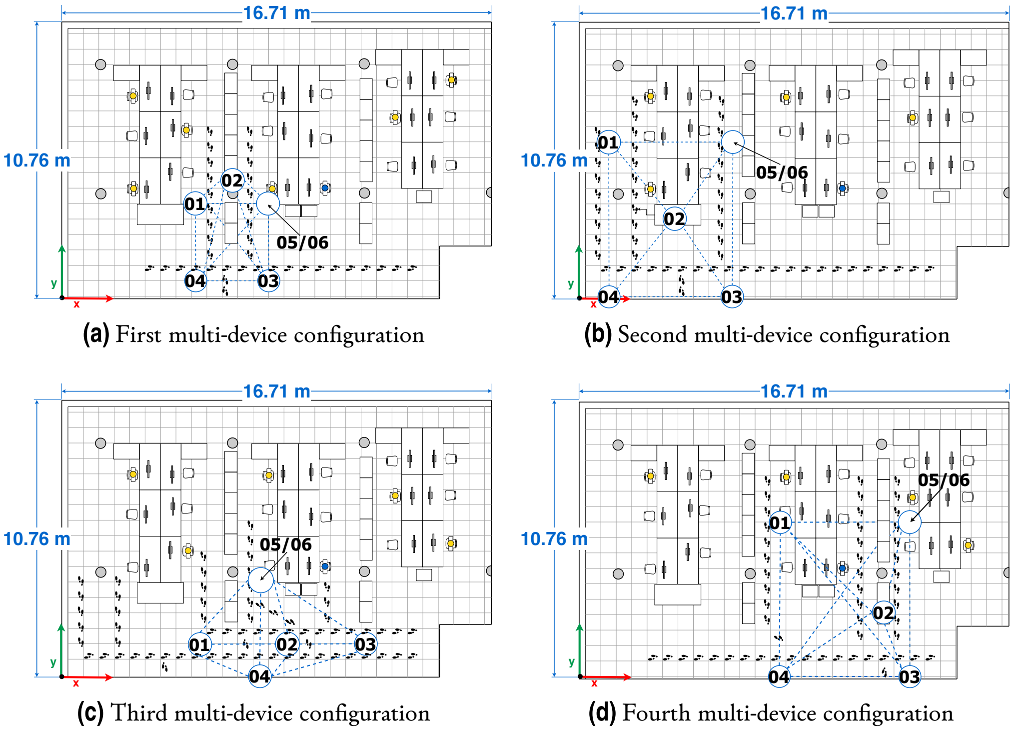
The data collection of Subset-B includes four configurations, which are illustrated in Figure 3.4. Each configuration is composed of five mobile devices, Galaxy S8 (01), Lenovo Yoga Book (02), Galaxy A7 Duos (03) Galaxy S6 (04), and Honor Lite (05). In each configuration, as illustrated in the sketches, only one person intentionally sits in front of the computer (blue person icon) in the office or walks through it (footprints paths) to create various NLOS conditions between devices. The configurations are fully described as follows:

- The first multi-device configuration, sketched in Figure 3.4(a), considers five mobile devices exchanging iBeacon advertisements. Nevertheless, the device pairs 01&03, 01&05, and 05&04 present NLOS due to two wooden bookcases, which obstruct the path signal between them. Furthermore, the LOS path signal between the device pair 02&03 is obstructed by a concrete column.

- The second multi-device configuration sketched in Figure 3.4(b), presents a geometric distribution that considers a mobile device (device 02) located equidistant from the other mobile devices (devices 01, 03, 04, and 05). On the one hand, the device pairs 03&02, 03&04, 03&05, and 02&04 present LOS. On the other hand, the device pairs 01&02, 01&05, and 02&05 are partially obstructed by a set of desks.
- The third multi-device configuration, sketched in Figure 3.4(c), presents a configuration in which device 02 blocks the signal traveling in LOS between devices 01 and 03. In addition, a wooden bookcase blocks the LOS path signal between the device pairs 01&05.
- In the fourth multi-device configuration, sketched in Figure 3.4(d), device 02 is situated on a wooden bookcase shelf, blocking the signal from its LOS path to devices 03 and 05, but preserving LOS conditions with devices 01 and 04. The pairs 01&05, 04&05 present NLOS and device pairs 01&04, 03&04, and 03&05 LOS conditions. A set of desks is located between the device pairs 01&02 and 01&03.

The data collection of Subset-C includes seven configurations, which are illustrated in Figure 3.4 and Figure 3.5. Each configuration includes five devices, Galaxy S8 (01), Lenovo Yoga Book (02), Galaxy A7 Duos (03) Galaxy S6 (04), and Galaxy A5 (06). Unlike Subset-B, in Subset-C the Honor 20 lite smartphone (05) was replaced by the device Galaxy A5 (06).

The first four multi-device configurations of Subset-C are similar to the ones presented in Figure 3.4 for Subset-B. However, the number of people inside the office and walking around increased (blue person icon plus orange person icons). In detail, 7 people were inside the office for the first configuration, 5, 6, and 5 people for the second, third, and fourth configurations, respectively. The change in the number of people occupying and walking in the office aims to more accurately represent the behavior of workers in an office environment and to observe how the transmission/reception of the signals are affected by them.



(a) First multi-device configuration
(b) Second multi-device configuration
(c) Third multi-device configuration
(d) Fourth multi-device configuration

Figure 3.4 Multi–device configurations (1 to 4) office scenario. Source [21].

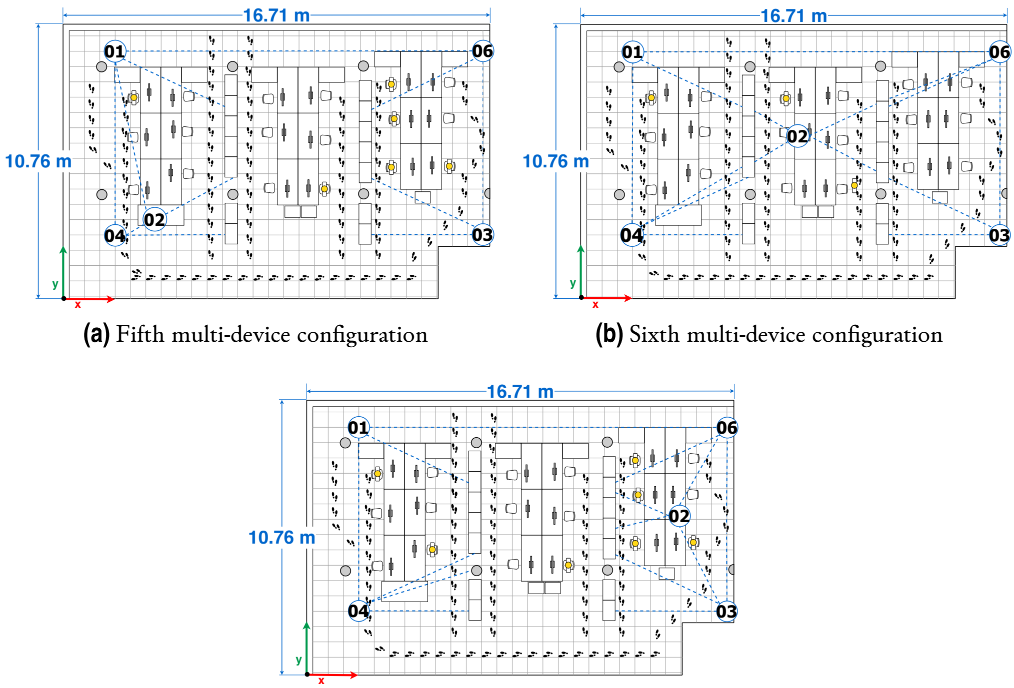
Regarding the fifth, sixth, and seventh multi-device configurations shown in Figure 3.5, we can notice that devices 01, 03, 04, and 06 are located in the same location, near to the office corners. However, mobile device 02 is located, in each configuration, at a different place.

In the fifth, sixth, and seventh multi-device configurations, the mobile devices 01, 03, 04, and 06 are located in the same location, near the office corners, as it can be seen in the sketches of Figure 3.5. The main difference between these configurations is the location of mobile device 02. Observing only the four devices located near corners, on the one hand, we notice that the device pairs 01&06, 01&04, and 03&06 present LOS conditions, on the other hand, the pairs 01&03, 03&04, and 04&06 present NLOS because of the central bookcases. In detail:

- In the fifth multi-device configuration, sketched in Figure 3.5(a), device 02 is located near device 04 and in LOS with devices 01 and 04. Furthermore, the central bookcases of the office blocked the LOS between device 02 and devices

03 and 06.

- In the sixth multi-device configuration, sketched in Figure 3.5(b), the LOS of device 02 with the devices placed on the corners (devices 01, 03, 04, and 06) is blocked by the central bookcases surrounding device 2.
- In the seventh multi-device configuration, sketched in Figure 3.5(c), device 02 is in LOS with the devices 03 and 06, but in NLOS with the devices 01 and 04 due to central bookcases.



(a) Fifth multi-device configuration

(b) Sixth multi-device configuration

(c) Seventh multi-device configuration

Figure 3.5 Multi–device configurations (5 to 7) office scenario. Source [21].

The raw data collection, for Subset-B and Subset-C, was conducted using the *Get-SensorsData* application for a period of 2 hours in each configuration. During the data collection, the mobile devices of each configuration simultaneously advertise their own BLE messages while reading/saving the information from all sensors, including the received advertisements emitted by surrounding devices and their RSSI. Hence, the raw data Subset-B contains 20 *logfiles* and Subset-C contains 35 *logfiles*. During the measurements, the people moving around the office, following the paths shown in each configuration (footprints depicted in Figure 3.4 and Figure 3.5), generate NLOS conditions between devices. Despite the desks set between mobile devices do not completely block the LOS, they create interference with the BLE signal propagation. It should be pointed out that each device's information storage is not synchronized. Nevertheless, the time latency, which is in the order of seconds, should not be a big drawback for static references.

The Table 3.4 reports the average with the standard deviation of the BLE measurements collected by the six mobile devices in the Subset-A (90 s windows), Subset-B (2 h windows), and Subset-C (2 h windows). BLE measurements emitted by external devices to the mobile devices included in the configurations have been excluded from Table 3.4. Overall, an average (with standard deviation) of1995 ± 731, 79121 ± 54443, and 97371 ± 30650 valid BLE measurements were recorded in Subset-A, Subset-B, and Subset-C, respectively. It should be noted that the recorded amount of BLE advertisement from a specific mobile device is related to the LOS/NLOS conditions, the distance between emitter and receiver, and the BLE hardware at the receiver side. Therefore, the number of BLE recorded can vary, which is represented by the standard deviation. Regarding the last case, from Table 3.4, we can notice that the Galaxy A5 is only receiving ≈ 2 BLE messages per receiver and second for the calibration collection in Subset-A, whereas the Galaxy S8 is receiving ≈ 2 BLE messages per receiver and second (×3 higher) in the same subset.

Table 3.3 Devices' Ground truth in each configuration of subset B and C. Source [21].

ID	Ground truth (m)														Subset
	Config. 1		Config. 2		Config. 3		Config. 4		Config. 5		Config. 6		Config. 7		
	x	y	x	y	x	y	x	y	x	y	x	y	x	y	
01	5.05	3.7	1.33	6.1	6.93	1.3	7.75	6.1	2.05	9.7	2.05	9.7	2.05	9.7	B&C
02	6.55	4.55	4.49	3.05	9.93	1.3	11.75	2.75	3.6	3.3	8.7	6.4	14.66	6.45	B&C
03	8.05	0.7	7.66	0.1	12.93	1.3	12.75	0.1	16.45	2.5	16.45	2.5	16.45	2.5	B&C
04	5.05	0.7	1.33	0.1	9.03	0.1	7.75	0.1	2.05	2.5	2.05	2.5	2.05	2.5	B&C
05	8.05	3.7	7.66	6.1	9.03	3.7	12.75	6.1	16.45	9.7	16.45	9.7	16.4	9.7	B
06	8.05	3.7	7.66	6.1	9.03	3.7	12.75	6.1	16.45	9.7	16.45	9.7	16.4	9.7	C

3.3 Database structure

The multi-device BLE-RSSI database is available at the Zenodo repository [23]. Its structure is illustrated through its directory tree and file structure in Figure 3.7. The database is divided into three major sub-directories, `Raw-Data`, `Processed-Data`,

Table 3.4 Average of BLE measurements collected by device in each 90s and 2 hours time windows. Source [21].

ID	Mobile name	Subset-A (90 s time window)	Subset-B (2 h time window)	Subset-C (2 h time window)
01	Galaxy S8	2776 ± 63	80695 ± 60174	81100 ± 32178
02	Lenovo Yoga Book	2604 ± 57	117095 ± 67440	135738 ± 9090
03	Galaxy A7 Duos	1389 ± 188	62281 ± 35708	77029 ± 6454
04	Galaxy S6	2309 ± 127	100933 ± 57994	121047 ± 11955
05	Honor 20 Lite	2004 ± 136	34602 ± 19596	–
06	Galaxy A5	887 ± 99	–	71941 ± 10164

and `Code`. On the one hand, the raw data directory comprises all data gathered, from the mobile device's sensors and wireless communications, with the *GetSensorsData* application. On the other hand, the processed data directory comprises the essential BLE data for ranging and collaborative positioning, which has been obtained by processing the raw data with the code provided.

The `Raw-Data` directory comprises the raw data of the three subsets A, B, and C detailed in Section 3.2, which are organized into sub-directories `Subset-A`, `Subset-B`, and `Subset-C` respectively. The sub-directories are structured similarly, with a sub-directory for each scenario. At present, only one scenario (office) raw data is included in the three subsets within the `Office` folder. Within each scenario directory, one or more sub-directories are included (i.e., configuration sub-directories). Within each configuration directory, sub-directories that correspond to each receiver device used to collect the data are included. Finally, within them, the raw data files from the independent data collections performed are included. For example, `Rawdata-A/Office/Config01/ReceiverDev01/*.txt` contains the raw data of subset A, office scenario, configuration Config01 and collected with device 01.

The `Processed-Data` directory comprises the BLE data and is organized similarly to the `Raw-Data`, considering the subset, scenario, configuration, and device as a hierarchical folder. The path `Processed-Data/Office/Config01/ReceiverDev01/MeasurementsBLE.csv` contains the processed data of the previous raw data example. Contrary to the files of raw data, the processed data files are saved as comma-separated values (CSV) files for each combination of the receiver, configuration, scenario, and subset.

The `Code` directory comprises the Matlab script files used for processing the raw data, generating the processed data, visualizing valuable information, and performing technical validations. Despite the database currently focusing on a single scenario (i.e., the office) and a few configurations (one for Subset-A, four for Subset-B, and Seven for Subset-C), the database has been planned to be readily expanded using the systematic structure that was introduced. The `Raw-Data`, `Processed-Data`, and `Code` sub-folders and files are described in detail below.

`Raw-Data` sub-folders:

- `Subset-A` consists of 1 scenario (`Office`), 1 configuration (`Config01`) and 6 receiver devices (`ReceiverDev01` to `ReceiverDev06`). Each nested sub-directory (`ReceiverDev01` to `ReceiverDev06`) contains 11 TXT raw data files. The files correspond to the measurements collected by each receiver device, at a particular reference point (1 m to 11 m), according to Configuration 01 in the office scenario. There is no need to change the file name for the *log-files* if the data is collected consecutively, beginning at 1 m and ending in 11 m. Overall, in `Subset-A`, 66 TXT raw data files are saved.
- `Subset-B` consists of 1 scenario (`Office`) and 4 configurations (`Config01` to `Config04`) and 5 receiver devices (`ReceiverDev01` to `ReceiverDev05`). Each nested sub-directory (`ReceiverDev01` to `ReceiverDev05`) contains 1 TXT raw data files. The file contains the raw data of the receiver device indicated by the sub-folder name. Overall, in `Subset-B`, 20 TXT raw data files are saved.
- `Subset-C` applies the same folders organization of `Subset-B` sub-directory, but considering 7 configurations (`Config01` to `Config07`) and 5 receiver devices (`ReceiverDev01` to and `ReceiverDev06`) sub-directories. There are 35 TXT raw data files in all.

`Processed-Data` sub-folders:

- `Subset-A` comprises 6 processed data files, saved in comma-separated values (CSV) format. The files are the result of processing the raw data. The data recorded, by the specific receiver, for each CSV file is 90 seconds long.
- `Subset-B` and `Subset-C` comprises 20 and 35 CSV processed data files respectively. The data recorded, by the specific receiver, for each CSV file is 2 hours long.

`Code` sub-directory contains the MatLab source code (4 main scripts):

- `ProcessMyRawData_ABC.m` script, processes the raw data, which is contained in the `Raw-Data` folder and saves the processed data into `Processed-Data`. The supporting scripts `dialogselectfolder.m`, `readrawfiles.m`, and `bleformat.m` are required in order to run this script.
- `Disp_distribution.m` displays the distribution of the subsets' processed data contained in `Processed-Data`;
- `Val_pathloss.m` and `Val_collab.m` are used for the technical validations of the data collected in LOS. In order to detail in depth, the use of all the scripts a `Readme.txt` file is provided.

In order to keep the files organized, we use the following file naming conventions. For CSV files, which correspond to the processed data, we named all of them as `MeasurementsBLE.csv`. The structure of CSV files row is organized as follows (see Figure 3.6):

- TestID: A six digits identifier used to distinguish the subset, scenario, configuration, and device used in the data collection.
- Timestamp: Indicates the time, in seconds, in which the *GetSensorData* application, installed on the receiving mobile device, reads the BLE packets transmitted by mobile devices used in the experiments.
- RSSI: Received Signal Strength Indicator (RSSI) value of mobile devices used in the experiments, in dBm, measured by the receiver device.
- Major: A two-digit identifier used to classify the mobile devices' BLE packets and distinguish them from other groups.
- Minor: A two-digit identifier used to classify the mobile devices' BLE packets within the group to which they belong.
- Ground Truth x: Specifies the mobile devices' real x coordinate in meters for each configuration in the office scenario.
- Ground Truth y: Specifies the mobile devices' real y coordinate in meters for each configuration in the office scenario.

For the *logfiles* with raw data (TXT files), the file name consists of three parts: first, an initial name ("logfile"); second, the date (yyyy_mm_dd); and third, the time (HH_MM_SS) of the end of the recording, all them separated by underscores. The

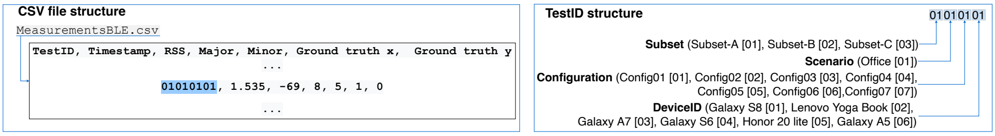


Figure 3.6 CSV file and TestID structure examples. Source [21].

information of BLE packets read is saved in the TXT file chronologically as they are received (one row per BLE packet) and each field in the row is divided by semicolons. The BLE packet fields saved are detailed as follows:

- Type of technology: An identifier set at the beginning of each row, indicates the type of sensor data measured. For the BLE case, the identifier is: “BLE4”.
- Timestamp: indicates the time, in seconds, in which the *GetSensorData* application, installed on the receiving mobile device, reads the BLE packets transmitted by mobile devices used in the experiments.
- Type of beacon: Specifies the beacon format read (“iBeacon”/“Eddystone”).
- MAC: The Media Access Control (MAC) of every device read by the *GetSensorData* application in the receiving mobile device.
- RSSI: Received Signal Strength Indicator (RSSI) value of mobile devices used in the experiments, in dBm, measured by the receiver device.
- Transmission Power: Specifies the transmission power, in dBm, of BLE packets.
- Major: A two-digit identifier used to classify the mobile devices’ BLE packets and distinguish them from other groups.
- Minor: A two-digit identifier used to classify the mobile devices’ BLE packets within the group to which they belong.
- UUID: The Universal Unique Identifier (UUID) is a unique number used to identify the devices’ BLE packets.

Additional details about the sensors data formats used on the *GetSensorData* application is available in [174, 175]. The remaining modules of the application remained unchanged from the original version, as was already noted, with the exception of the added broadcasting BLE advertisements.

```
Collaborative_dataset
├── Raw-Data ........................ Contains the raw data of subset A, B, and C
│   ├── Subset-A ........................ Contains the raw data collected from the LOS experiments in the indoor environment (office scenario)
│   │   └── Office
│   │       └── Config01 ...  This sub-directory holds the raw data files, Receiver devices 01 to 06,
│   │           │             in accordance with the LOS Configuration 01.
│   │           └── ReceiverDev<ID>
│   │               └── logfile_yyyy_mm_dd_HH_MM_SS.txt
│   ├── Subset-B ........................ Contains the raw data collected from 4 configurations (office scenario)
│   │   └── Office
│   │       └── Config<nB> ...  This sub-directory holds the raw data files, Receiver devices 01 to 05,
│   │           │               in accordance with the collaborative configuration <nB>.
│   │           └── ReceiverDev<ID>
│   │               └── logfile_yyyy_mm_dd_HH_MM_SS.txt
│   └── Subset-C ........................ Contains the raw data collected from 7 configurations (office scenario)
│       └── Office
│           └── Config<nC> ...  This sub-directory holds the raw data files, Receiver devices 01 to 04,
│               │               and 06, in accordance with the collaborative configuration <nC>.
│               └── ReceiverDev<ID>
│                   └── logfile_yyyy_mm_dd_HH_MM_SS.txt
├── Processed-Data ........................ Contains the processed data of subset A, B, and C
│   ├── Subset-A ........................ Contains the processed calibration data obtained from the LOS experiments in the indoor environment (office scenario)
│   │   └── Office
│   │       └── Config01 ...  This sub-directory holds the processed measurements files, Receiver
│   │           │             devices 01 to 06, in accordance with the LOS Configuration 01.
│   │           └── ReceiverDev<ID>
│   │               └── MeasurementsBLE.csv
│   ├── Subset-B ........................ Contains the collaborative positioning processed data obtained from 4 configurations (office scenario)
│   │   └── Office
│   │       └── Config<nB> ...  This sub-directory holds the measurements files, Receiver devices 01 to
│   │           │               05, in accordance with the collaborative Configuration <nB>.
│   │           └── ReceiverDev<ID>
│   │               └── MeasurementsBLE.csv
│   └── Subset-C ........................ Contains the collaborative Positioning processed data obtained from 7 configurations (office scenario)
│       └── Office
│           └── Config<nC> ...  This sub-directory holds the measurements files, Receiver devices 01 to
│               │               04, and 06, in accordance with the collaborative Configuration <nC>.
│               └── ReceiverDev<ID>
│                   └── MeasurementsBLE.csv
└── Code ........................ Contains the source code used for the creation of the Dataset, its visualization, and the technical validation examples
    ├── Readme.txt
    ├── ProcessMyRawdata_ABC.m
    ├── Disp_distribution.m
    ├── Val_pathloss.m
    ├── Val_collab.m
    ├── dialogselectfolder.m
    ├── readrawfiles.m
    └── bleformat.m
```

Figure 3.7 Directory tree of the database. <nB>∈{01,...,04} and <nC>∈{01,...,07}. Source [21].

3.4 Technical validation

This subsection presents an example to demonstrate the usefulness of the previously described database. The example consists of a lateration approach considering collaborative users, which uses the data of Subset-B and Subset-C.

3.4.1 Lateration approach based on collaborative users

To validate the data contained in Subset-B and Subset-C, we present a collaborative positioning approach, which uses the data corresponding to the first, second, and third collaborative configurations (see Figure 3.4(a), Figure 3.4(b), and Figure 3.4(c)) and saved by the Device 02. It should be noted that the data used in this technical validation have been restricted to only those three configurations due to the high data volume of subsets B and C. In detail, the path folder of the six files used in this validation (one per subset and collaborative configuration) are as follows:

- `/Processed-Data/Subset-B/Office/Config01/ReceiverDev02/MeasurementsBLE.csv`
- `/Processed-Data/Subset-B/Office/Config02/ReceiverDev02/MeasurementsBLE.csv`
- `/Processed-Data/Subset-B/Office/Config03/ReceiverDev02/MeasurementsBLE.csv`
- `/Processed-Data/Subset-C/Office/Config01/ReceiverDev02/MeasurementsBLE.csv`
- `/Processed-Data/Subset-C/Office/Config02/ReceiverDev02/MeasurementsBLE.csv`
- `/Processed-Data/Subset-C/Office/Config03/ReceiverDev02/MeasurementsBLE.csv`

In this technical validation, we assume a collaborative scenario composed of five users (Users 1–5), each of them holds a mobile device. Specifically, Mobile devices 01–05 for Subset-B and Mobile devices 01-04, and Mobile device 06 for Subset-C. Also, we assume that Users 1 and 3–5 know their exact position (e.g., using a position approach based on Ultra-Wideband (UWB)) and share it (e.g., using a centralized platform) with User 2, which, in contrary to devices 1 and 3–5, is not able to self-determine its position with high accuracy. So, considering the exact position, the dataset makes it possible to assess collaborative positioning methods without the added accumulated error that the predicted positions would introduce. In order to determine its own location through collaborative methods, User 2 uses the position information of Users 1 and 3–5 and the estimated relative distances to them (based on the RSSI values and Path Loss model). Despite the fact that this collaborative scenario seems to represent a classical positioning scenario, which uses Users 1 and 3–5 as regular beacons, the variety of hardware (at the level of smartphones and Bluetooth chipsets) and software (at the level of operating system versions and vendor's customization layer) used makes this positioning more difficult.

Figure 3.8 presents the workflow for the collaborative method and is detailed as follows:

- **1st step:** Select the user (i.e., User 2) and load the registered data of the remaining devices (Users 1 and 3–5) registered on the user's device;
- **2nd step:** Cluster the RSSI values by device (Users 1 and 3–5) and obtain their position from the centralized platform;

- **3rd step:** Cluster the RSSI values into $60\,\mathrm{s}$ bins;
- **4th step:** Smooth the noisy RSSI and remove its outliers using a moving average of 30 samples;
- **5th step:** To get only one RSSI value per device in each time interval (Bin), average them considering the interval of time specified in the first step;
- **6th step:** Estimate the distances, between User 2 and Users 1 and 3–5, considering the LDPL (see eq. 4.1) and the averaged RSSI values from 4th step. The path-loss attenuation factor (η) used for Users 1 and 3–5 are 0.6, 1.01, 0.61, and 1.03 and the $RSSI(d_0)$ equal to $-77.39\,\mathrm{dBm}$, $-67.97\,\mathrm{dBm}$, $-75.36\,\mathrm{dBm}$ and $-64.33\,\mathrm{dBm}$ respectively, and
- **7th step:** Estimate the User 2 position considering the Levenberg-Marquardt Least Squares (L-MLS) lateration method, which inputs are the distances estimated in the fifth step, position of Users 1 and 3–5, and user' weights (inverse of their distance square).

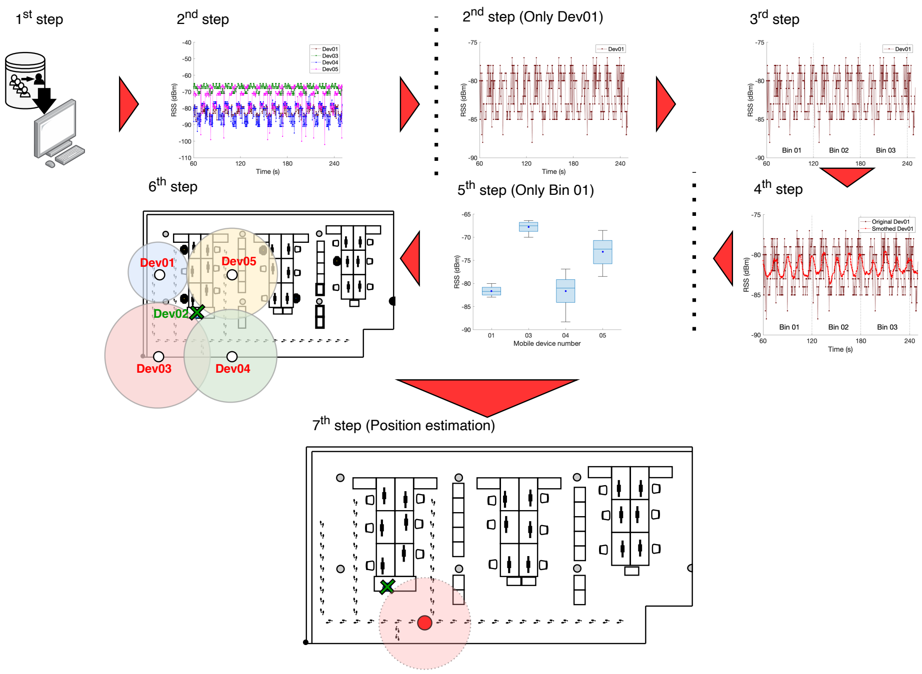


Figure 3.8 Collaborative positioning approach workflow. Source [21].

Table 3.5, summarizes, through several metrics based on User 2's positioning error, the results of the collaborative approach.

Table 3.5 Statistical values of the Euclidean distance error of each collaborative scenario example. Source [21].

Subset	Conf.	$Mean$ (m)	$Median$ (m)	P_{25} (m)	P_{75} (m)
B	01	1.72	1.75	1.68	1.78
C		0.60	0.61	0.55	0.66
B	02	4.08	3.77	3.54	4.78
C		3.33	3.54	2.23	4.42
B	03	1.87	1.78	1.58	2.07
C		1.02	0.94	0.44	1.47

In detail, the results of collaborative configurations 01 and 03 demonstrated that the proposed collaborative approach accurately estimates the position in conditions of moderate NLOS and the short distance between the user and the target user (i.e., User 2). Nevertheless, the results of configuration 2 (large and equidistant distance between devices) presented the largest mean euclidean distance error, $4.08\,\mathrm{m}$ and $3.33\,\mathrm{m}$ due to two cases, the deliberate and frequent walking of workers in the office (prolonged NLOS) and for walking more moderately in the office, respectively. It should be noted that the presented positioning strategy just served to validate the collected dataset. Additional improvements, e.g., more robust filters and dynamics parameters selection, could improve the accuracy and robustness of the method proposed. Nevertheless, this is outside the scope of this section.

3.5 Database extensions

Collaborative indoor positioning approaches involve various aspects to be taken into account for their design, evaluation, and implementation. For example, signal propagation between mobile devices in LOS and NLOS conditions, unstable signal propagation due to environmental conditions (e.g., geometries, wall materials, furniture, diverse sources of wireless transmission), the variation of RSSI values and the estimation of the distance between devices due to the use of heterogeneous collaborative mobile devices, effects of the distribution of beacons in the environment, among others. Therefore, in order to extend the analysis and evaluation of the aforementioned aspects of collaborative approaches, additional configurations and scenarios were considered. The following subsections describe them.

3.5.1 New Scenario: The lobby scenario

Additional to the office scenario described in 3.2.2, we included a new scenario –the lobby scenario. The lobby scenario is located on the second floor of the Tietotalo building at Tampere University (Tampere, Finland). The scenario has an approximate area of $26.2\,\mathrm{m}$ by $13.7\,\mathrm{m}$ and includes 7 concrete pillars, seater sofas, an office pod, tables, and lecture desks as illustrated in Figure 3.9. The lobby scenario, similar to the office scenario, provides rich NLOS and complex conditions. This new scenario was used to extend the ranging collaborative dataset (see Section 3.5.2) and create a Wi-Fi radio map (see Section 3.5.3.2). Moreover, we used the scenario and the data of the two sections previously mentioned to experimentally evaluate and validate the collaborative approach presented in Section 5.3.

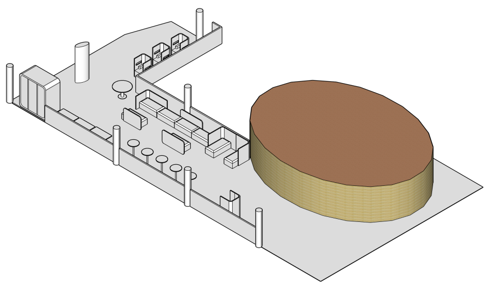


Figure 3.9 3D lobby scenario representation.

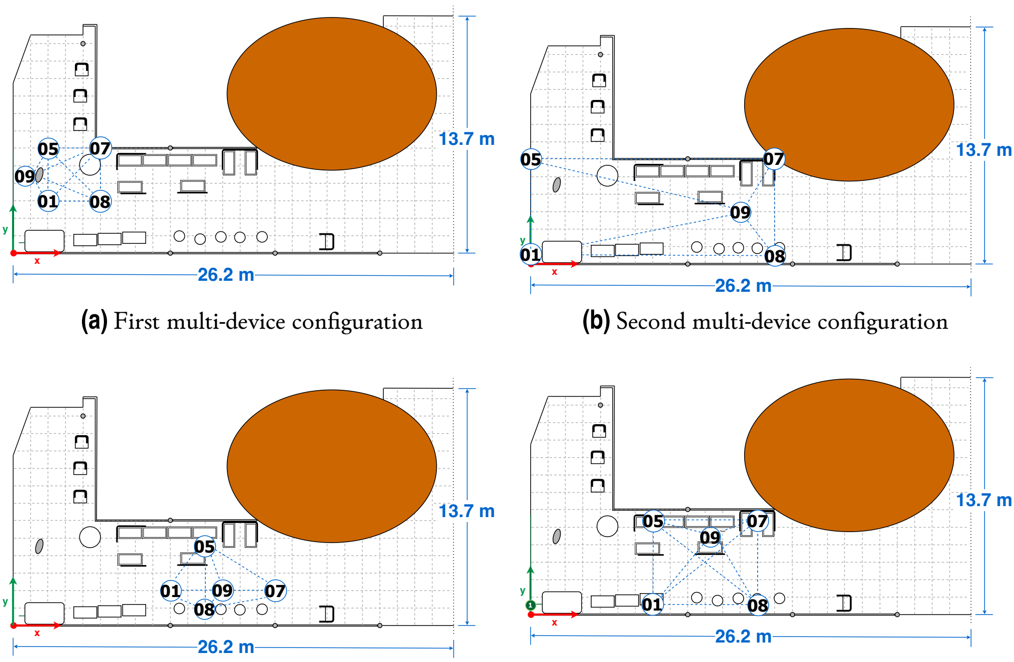
3.5.2 Extended ranging collaborative dataset

The BLE data collection of the lobby scenario was done considering the same methodology and database structure explained in Section 3.2 & 3.3 (Subset C) respectively, but applied to different configurations and using different mobile devices. In the data collection, we included six configurations, which are illustrated in Figure 3.10 and Figure 3.11. Each configuration is made up of five mobile devices, of which 2 (Galaxy S8 and Honor Lite) were also used in the experiments in the office scenario, and 3 (Galaxy S6 Edge, Huawei P40, Lite, and Galaxy A12) are only used in this one. Table 3.6 lists the mobile devices, sorted by ID number, and details the configuration data for the mobile devices used in the data collection procedure. In detail, the configurations are described as follows:

- The first multi-device configuration, sketched in Figure 3.10(a), considers five mobile devices exchanging iBeacon advertisements. The distance between each pair of devices is short in comparison with the other configurations, less than $4\,\mathrm{m}$. Nevertheless, the device pairs 07&09 and 08&09 present NLOS due to a concrete pillar, which obstructs the path signal between them.
- The second multi-device configuration, sketched in Figure 3.10(b), presents a geometric distribution that considers a mobile device (device 09) located near mobile devices (devices 07 and 08). On the one hand, the device pairs 01&05, 05&09, and 08&09 present LOS. On the other hand, the device pairs 01&09, 01&08, 01&07 are obstructed by an office pod, the device pair 05&07 by a concrete pillar, and 07&09 by a seater sofa.
- The third multi-device configuration, sketched in Figure 3.10(c), presents a configuration in which device 09 blocks the signal traveling in LOS between devices 01 and 07. In addition, a seater sofa partially blocks the LOS path signal between the device pairs 01&05.
- In the fourth multi-device configuration, sketched in Figure 3.10(d), device 09 is situated between seater sofas, which partially blocks the signal from its LOS path to devices 01, 08, and 07, but preserves LOS conditions with device 05. The device pair 01&08 has LOS between them and the device pair 01&08 the LOS is partially blocked by seater sofas. Also, device 07 is located within two-seater sofas, which block the LOS with devices 05, 01, and 09, but has LOS with device 08.
- The fifth multi-device configuration, sketched in Figure 3.11(a), presents a geometric distribution that considers a mobile device (device 09) located near mobile devices (devices 01 and 05). The device 09 has LOS with devices 01, 05, and 08, but NLOS with device 07. The device pairs 01&08, 01&07, and 05&07 present NLOS condition and devices pairs 01&05 and 07&08 LOS condition.
- The sixth multi-device configuration, sketched in Figure 3.11(b), presents a geometric distribution that considers a mobile device (device 09) located equidistant from the other mobile devices (devices 01, 05, 07, and 08). Device 09 is in LOS with devices 05 and 08 and in NLOS with devices 07 and 01.

Table 3.6 iBeacon identifiers of each mobile device used in lobby scenario.

ID	Mobile name	UUID	Major	Minor
01	Galaxy S8	94339309-BFE2-4807-B747-9AEE23508620	8	1
05	Honor 20 Lite	94339309-BFE2-4807-B747-9AEE23508620	8	5
07	Galaxy S6 Edge	94339309-BFE2-4807-B747-9AEE23508620	8	7
08	Huawei P40 Lite	94339309-BFE2-4807-B747-9AEE23508620	8	8
09	Galaxy A12	94339309-BFE2-4807-B747-9AEE23508620	8	9



(a) First multi-device configuration

(b) Second multi-device configuration

(c) Third multi-device configuration

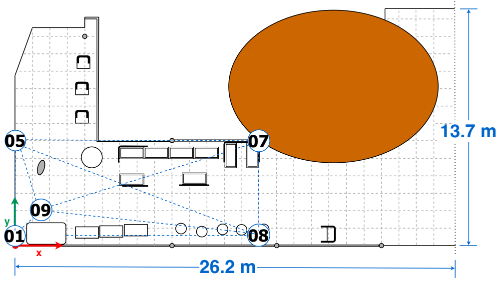
(d) Fourth multi-device configuration

Figure 3.10 Multi–device configurations (1 to 4) lobby scenario.

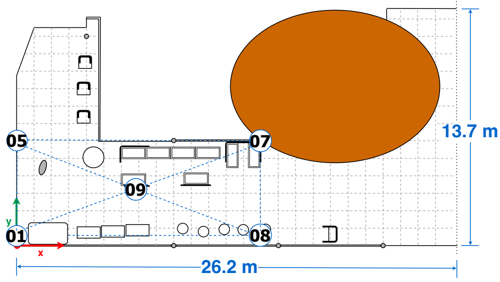
Table 3.7 Devices' Ground truth in each configuration used in the lobby scenario.

ID	Ground truth (m)											
	Config. 1		Config. 2		Config. 3		Config. 4		Config. 5		Config. 6	
	x	y	x	y	x	y	x	y	x	y	x	y
01	2	3	0	0.5	9	2	6	0.5	0	0.5	0	0.5
05	2	6	0	6	11	4.5	6	5.5	0	6	0	6
07	5	3	14	6	15	2	12	5.5	14	6	14	6
08	5	6	14	0.5	11	1	12	0.5	14	0.5	14	0.5
09	1	4.5	12	3	12	2	9.5	4.5	1.5	2	7	3

In addition to the LOS and NLOS conditions and geometries of the environment, the configurations also present different distances between device pairs. For example,



(a) Fifth multi-device configuration



(b) Sixth multi-device configuration

Figure 3.11 Multi–device configurations (5 and 6) lobby scenario.

the first and third configurations are a short distance, the fourth a medium distance, and the second, fifth, and sixth a large distance. The ground truth of the mobile devices in each configuration is presented in Table 3.7.

3.5.3 Radio maps for fingerprinting

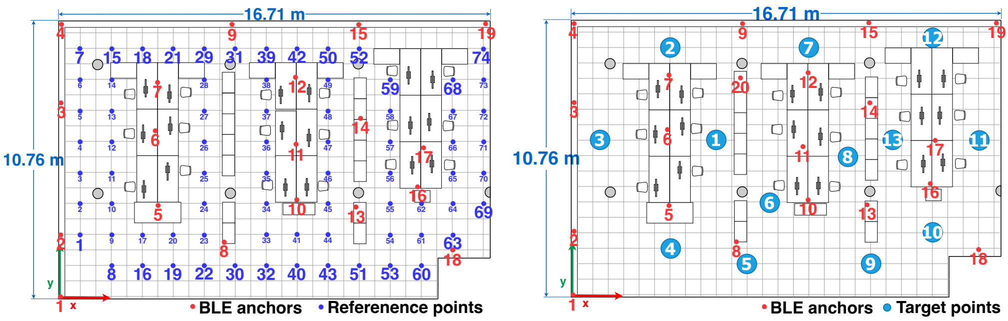
In order to complement the data collection for ranging and collaborative positioning between collaborative mobile devices and experimentally evaluate and validate our approaches presented in Chapter 4 and Chapter 5, we included three radio maps for positioning the collaborative mobile devices using the BLE anchors deployed in the office scenario and the Wi-Fi Access Points (APs) available in the lobby scenario. The objective of these new positioning databases is to provide the necessary data to estimate the position of collaborative mobile devices in the non-collaborative phase (see Section 5.3.2) of CIPSs through methods such as lateration and fingerprinting–*k*-Nearest Neighbors (*k*-NN). Also, to analyze the effect of adequate BLE anchors to improve the positioning accuracy. Specifically, the first BLE radio map presented in Section 3.5.3.1, was used to estimate the position of mobile devices in both the non-collaborative phase (initial position) of the CIPS proposed and the stand-alone BLE–fingerprinting approach used in Section 5.3. The second BLE radio map presented in Section 3.5.3.1 was used to experimentally evaluate and validate the lateration BLE–RSSI method based on combinatorial BLE anchor selection presented in Section 4.2.1 and in [6]. The Wi-Fi radio map presented in Section 3.5.3.2 was used to estimate the position of mobile devices in both the non-collaborative phase (initial position) of the CIPS proposed and the stand-alone Wi-Fi–fingerprinting approach used in Section 5.3. Moreover, theWi-Fi radio map, was used to experimentally evaluate the fingerprinting-based positioning system presented in Section 4.2.3.

It should be noted the importance of the radio maps presented in this section because one of the two CIPSs presented in Chapter 5 aims to enhance the positioning accuracy of traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting approaches, as well as our CIPS rely on fingerprinting approach in its no-collaborative phase. The following subsections describe each of the new radio maps.

3.5.3.1 BLE radio maps in the office scenario

In the office scenario, 19 BLE anchors were deployed and 74 reference points were set to collect the BLE–RSSI values. The transmission power and transmission period were set at $-4\,\mathrm{dBm}$ and $250\,\mathrm{ms}$ respectively. Figure 3.12 (a) illustrates the distribution of the 19 BLE anchors (red points) and 74 references points (blue points) used to build the BLE fingerprint radio map. The radio map was collected using each mobile device used in the six configurations described in Section 3.5.2. This radio map was used to estimate the position of mobile devices in both the non-collaborative phase (initial position) of the CIPS proposed and the stand-alone BLE–fingerprinting approach used in Section 5.3, and mentioned in the experiment section (Section 5.3.4.1).

Additionally to the BLE radio map described before, we built a new configuration considering only 13 target points, carefully distributed around the office scenario, to provide LOS and NLOS conditions with respect to the 20 BLE anchors deployed. Figure 3.12(b) illustrated the distribution of the 20 BLE anchors and 13 target points (blue circles) around the office scenario and Table 3.8 the Ground-Truth (GT) of BLE anchors and the 13 target points. A unique mobile device (Galaxy A5) was used to get the BLE RSSI data in each reference point. At each reference point, we recorded data for 10 minutes. This configuration is used to analyze the effect of adequate BLE anchors selection to estimate position using lateration in Section 4.2.1 and in [6].



(a) BLE radio map (fingerprinting) **(b)** BLE radio map (lateration)

Figure 3.12 Distribution of BLE anchors and radiomap reference/target points in the office scenario.

3.5.3.2 Wi-Fi radio map in the lobby scenario

In the lobby scenario, we did not deploy any infrastructure, but instead reused 67 MACs of the Wi-Fi APs available in the scenario and set 136 reference points where the Wi-Fi–RSSI values were collected. The mobile device Galaxy A12 was used to get the Wi-Fi–RSSI data in each reference point. At each reference point, we recorded

Table 3.8 Ground truth of BLE anchors and target points.

	Reference BLE anchors				Target points	
No.	x (m)	y (m)	TX Power (dB)	TX Period (ms)	x (m)	y (m)
1	0	0	-4	250	5.95	6.1
2	0	2.61	-4	250	3.85	9.6
3	0	7.66	-4	250	1.15	6.1
4	0	10.68	-4	250	3.85	1.9
5	3.88	3.54	-4	250	6.85	1.3
6	3.78	6.51	-4	250	7.75	3.7
7	3.87	8.64	-4	250	9.25	9.6
8	6.45	2.13	-4	250	10.75	5.5
9	6.68	10.64	-4	250	11.65	1.3
10	9.2	3.7	-4	250	14.05	2.5
11	9.08	5.95	-4	250	15.85	6.1
12	9.18	8.71	-4	250	14.05	10
13	11.4	3.6	-4	250	12.55	6.1
14	11.54	7.18	-4	250	–	–
15	11.54	10.65	-4	250	–	–
16	13.95	4.34	-4	250	–	–
17	14.2	6.05	-4	250	–	–
18	15.65	1.71	-4	250	–	–
19	16.65	10.65	-4	250	–	–
20	6.66	8.58	-4	250	–	–

data for 90 seconds. Figure 3.13 illustrated the distribution of the 136 reference points (blue points). The points cover the area where the six multi-device configurations were placed. The Wi-Fi radio map was used to estimate the position of mobile devices in both the non-collaborative phase (initial position) of the CIPS proposed and the stand-alone Wi-Fi–fingerprinting approach used in Section 5.3. Moreover, the Wi-Fi radio map, was used to experimentally evaluate the fingerprinting-based positioning system presented in Section 4.2.3.

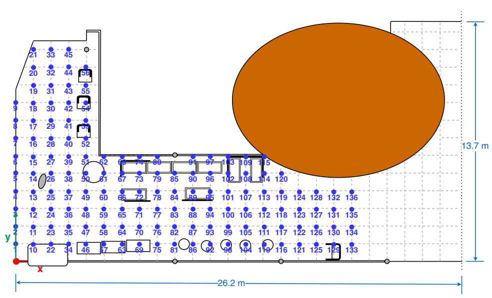


Figure 3.13 Radio map references points in the lobby scenario.

3.6 Chapter summary and discussion

In this chapter, we presented a mobile device-based BLE database for testing ranging collaborative indoor positioning approaches, considering bidirectional and simultaneous transmission/reception between devices. The data was collected experimentally in two real indoor scenarios (office and lobby) considering different mobile devices diversely distributed (configurations) in the scenarios. To guarantee the usability, reproducibility, and extension of the database, we provided the code used, as well as a detailed description of the structure of the database and the methodology used for data collection and processing. To validate the usefulness of the database an illustrative example of lateration approach based on collaborative users was provided.

In addition to the aforementioned database, we presented and describe three radio map collections performed in the office and lobby scenarios. The information provided by the radio maps (Wi-Fi and BLE fingerprint) is used to estimate the position of a collaborative mobile device. The data contained in the mobile device-based BLE database together with the BLE and Wi-Fi radio maps of the office and lobby scenarios of this chapter were used to evaluate and analyze the approaches proposed in Chapter 4 and Chapter 5.

4 DISTANCE AND POSITION ESTIMATION APPROACHES FOR MOBILE DEVICES

Nowadays, mobile/wearable devices incorporate diverse wireless technologies (e.g., IEEE 802.11 Wireless LAN (Wi-Fi), Bluetooth Low Energy (BLE), 5G, LTE, among others). Among them, Wi-Fi and BLE are widely adopted for position estimation. Accordingly, with the results reported in our systematic review (see Chapter 2), in Collaborative Indoor Positioning Systems (CIPSs), the first is used in both collaborative and non-collaborative parts, whereas the second is primordially used in the collaborative part. Moreover, such technologies are commonly coupled with Received Signal Strength Indicator (RSSI) and fingerprinting techniques. Within the methods implemented based on such technologies, the most common are RSSI-lateration and fingerprinting-k-Nearest Neighbors (k-NN) due to their easy implementation, capability to use the technologies and measurements on mobile/wearable devices, and acceptable accuracy [180]. Thus, we considered the aforementioned methods as basis for developing the algorithms used in our CIPSs and in the traditional Indoor Positioning System (IPS) presented in Chapter 5.

The RSSI-lateration methods to estimate the position require knowing the position of reference anchors distributed in the environment. That information is used first to estimate the relative distance between the unknown target to the reference anchors and then to estimate the target's position. Thus, a proper method to estimate the relative distance between anchor-target and to select the anchors with an adequate distribution is vital for accurate position estimation. In the case of fingerprinting–k-NN methods, in addition to data-representation and distance metric, two remarkable factors that affect their accuracy are the number of anchors and the number of neighbors considered (i.e., k value in k-NN).

The main contributions of this chapter are:

- We describe and experimentally evaluate the traditional methods to estimate distance (i.e., based on Logarithmic Distance Path Loss (LDPL) model and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-NN). Also, we present their limitations and challenges.

- We present a distance estimator based on the LDPL model and experimentally analyze, in an indoor environment, its performance considering heterogeneous mobile devices.
- We propose an innovative and straightforward system based on a fuzzy classifier to improve the accuracy and robustness of the LDPL model. Additionally, we experimentally demonstrate its practicality in enhancing positioning accuracy.
- We propose an innovative lateration BLE–RSSI method based on combinatorial anchors selection to enhance the accuracy and reliability of the position estimation. Furthermore, we demonstrate its effectiveness in improving the accuracy and reliability of position estimation.
- We present a fingerprinting–k-NN method for indoor positioning and experimentally analyze the effect of variations of the number of anchors and k-NN values on positioning accuracy.

4.1 Distance estimation

In addition to using wireless technologies embedded in mobile/wearable devices in communication systems, we can use them to estimate the relative distance between the transmitter and the receiver. There are various techniques (e.g., Time of Arrival (ToA), Angle of Arrival (AoA), RSSI) used in mobile/wearable devices to calculate the distance between them. However, one of the most widely used techniques is RSSI, because it is based on RSSI values [181], which are the simplest measurement that we can obtain from a received signal and are usually provided by the operative systems of mobile/wearable devices.

To estimate the distance based on RSSI, we use the correlation between the attenuation of RSSI as it propagates through space and the distance between transmitter and receiver [182]. However, the estimation computed by that approach is affected by various environmental factors (e.g., geometries, obstacles, etc.), hardware heterogeneity (e.g., transmit power, antenna gain, etc.), and well-identified signal propagation issues (e.g., multipath fading, reflection, refraction, diffraction) [165]. Therefore, providing a suitable model that accurately models the Radio Frequency (RF) wave propagation in various environmental conditions and reduces the impact of RSSI fluctuations on distance estimates is an open challenge.

4.1.1 Logarithmic Distance Path Loss (LDPL) model

The propagation of BLE signals in the environment, as part of RF signals, are not excluded from the error sources inherent to the aforementioned RF wave propagation, which add inaccuracy in the estimation of distance. Among the most used models for modeling the RF wave propagation and its correlation with the distance between transmitter and receiver, the two-ray ground, free space, and LDPL models are the most used [182, 181, 4]. This section considers the latter model due to its general use and straightforward implementation. However, setting the proper model parameters that accurately estimate distance in indoor environments, even in Line-of-sight (LOS), is a difficult task.

The main goals of this section are: first, to accurately estimate the distance between transmitter and receiver devices based on the LDPL model and proper setting of its parameters. Second, to analyze the behavior of the BLE signal propagation at different reference distances in an indoor environment and under LOS conditions. Third, under the same conditions, evaluate the impact of using heterogeneous transmitters on the model's parameters and the distance estimation accuracy.

In order to compute the distance between the transmitter and receiver considering the RSSI values in dBm, we use the LDPL model [165, 36, 183] expressed in the Eq. 4.1.

$$RSSI(d) = RSSI(d_0) - 10\eta \log\left(\frac{d}{d_0}\right) \tag{4.1}$$

where $RSSI(d)$ denotes the RSSI value measured at a distance d. Specifically, d is the distance between transmitter and receiver devices; $RSSI(d_0)$ denotes the RSSI at a reference distance d_0, typically $d_0 = 1\,\mathrm{m}$; η is a path-loss attenuation factor. The units used for RSSI and distances values are decibels (dBm) and meters (m), respectively.

It should be noted that adequate calibration in real-world environments positively impacts the accuracy of distance and position estimates based on LDPL. While calibration measurements are valid for the specific scenario and devices used, the calibrated parameters can also be applied to similar scenarios with the same devices. However, if the scenario changes significantly over time, periodical recalibration will be required to preserve the accuracy.

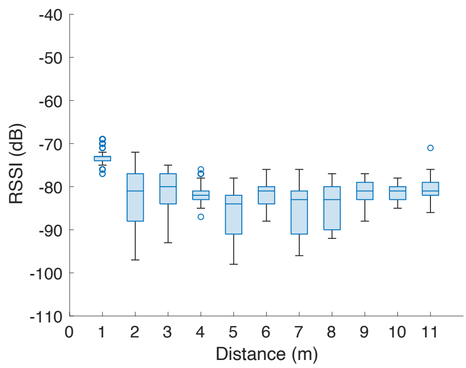
4.1.1.1 Experiments and results

With the experiment, we aim to achieve four objectives. The first objective consists of training or modeling the distance estimator based on the LDPL model to accurately determine the model's parameters ($RSSI(d_0)$ and η). Second objective is to estimate the distance between the receiver and the transmitters. Third objective is to analyze, under LOS conditions, the propagation behavior of the BLE signal transmitted by various transmitting devices and measured at different distance points. Fourth objective is to evaluate the effect of the use of heterogeneous transmitters causes on the model's parameters and the distance estimation accuracy.

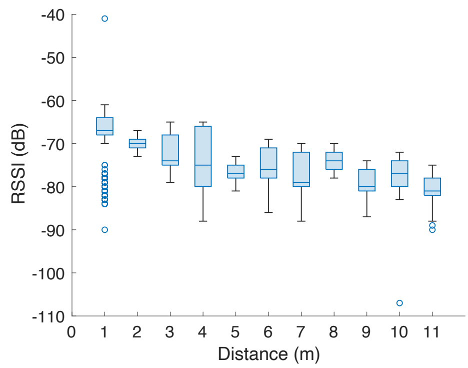
To achieve the aforementioned goals, we consider as input the calibration data (RSSI values) contained in the Subset-A (Config01) of the mobile device-based BLE database presented in Chapter 3. The data collection of Subset-A (Config01) was performed in an office scenario and measured in LOS. Its setup consists of 12 reference points, which were set on the floor of the main corridor of the office scenario every $1\,\mathrm{m}$ in a straight line and in LOS. On the initial point ($0\,\mathrm{m}$), we set the devices that act as transmitters and the device that acts as the receiver consecutively set at the reference points located at $1\,\mathrm{m}$ to $11\,\mathrm{m}$. Specifically, we use the data gathered with the receiver Device 02; Devices 01, 03, 04, and 05 act as transmitters. The setup and the office scenario are shown in Figure 3.3. Additional details about the Subset-A and office scenario are described in Section 3.2.3 and Section 3.2.2, respectively.

Figure 4.1 presents four box-plots, which show the distribution of the RSSI values of the Subset-A (Config01) collected with the Device 02 (receiver) on each reference point, every $1\,\mathrm{m}$ from $1\,\mathrm{m}$ to $11\,\mathrm{m}$, and transmitted with the Device 01, 03, 04 and 05. In detail, the x-axis and y-axis in each box plot represent the reference points distance where Device 02 (receiver) measured the RSSI and the RSSI values, respectively. In addition, at each reference point, the box plots display the data distribution using the minimum, first quartile, median, third quartile, and the data outliers.

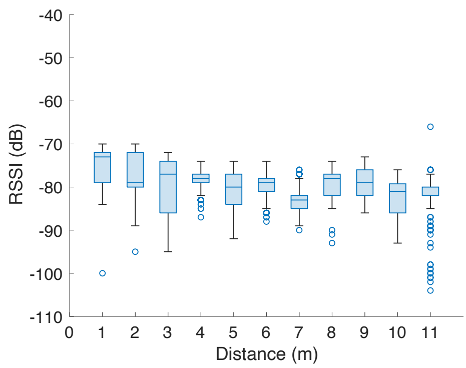
As it can be noticed in Figure 4.1, the RSSI measurements are very noisy even in LOS conditions. So, a filtering process, data smoothing, and reduction of the



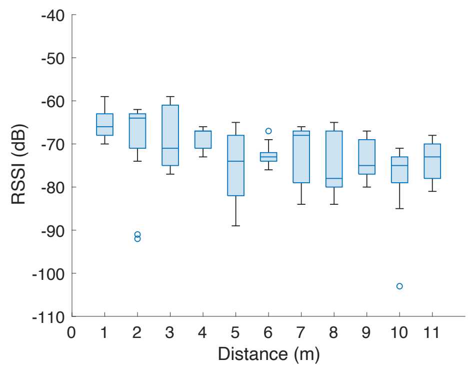
(a) Device 01 as transmitter



(b) Device 03 as transmitter



(c) Device 04 as transmitter



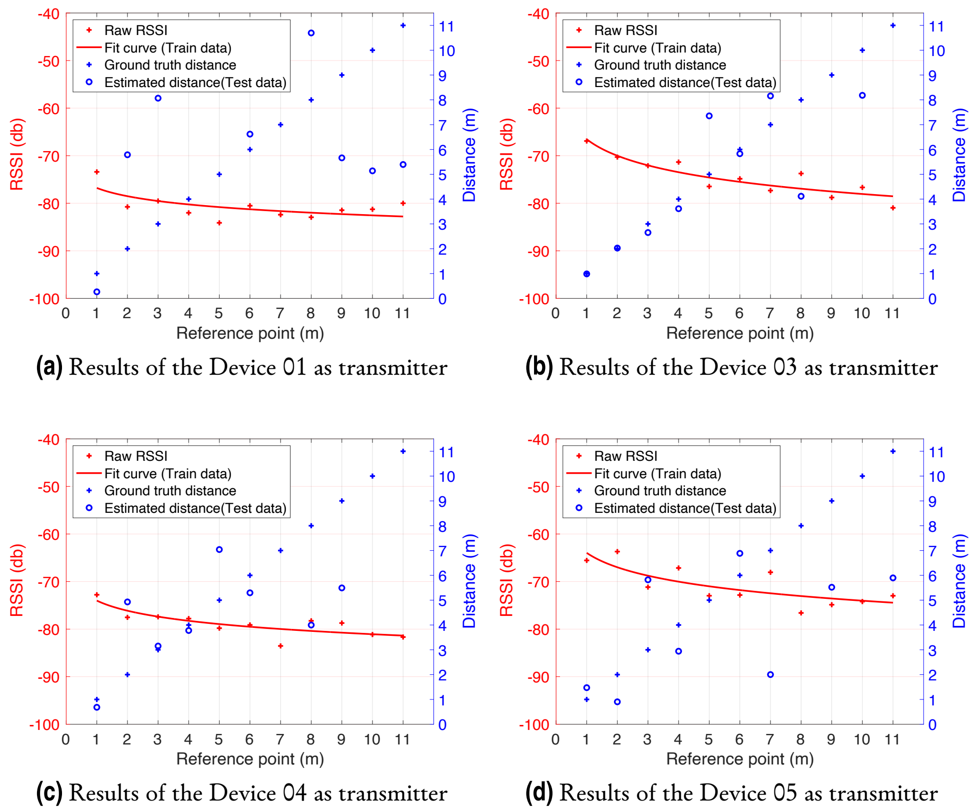
(d) Device 05 as transmitter

Figure 4.1 Distribution of the RSSI values of the Subset-A (Config01) collected with the Device 02 (receiver) on each reference point. Source [21].

effects of the outliers are needed before training the model. The filters used are the moving average, Robust Locally Weighted Scatterplot Smoothing (RLOWESS), and moving median, which takes into account 30 samples. Also, a sample averaging for each reference point was conducted. After that, to optimize the LDPL model parameters ($RSSI(d_0)$ and η), we applied a curve fitting to the data based on the non-linear least squares method.

The raw RSSI values filtered (red crosses) by a moving average filter are shown in Figure 4.2. Also, we present the fitting curve (solid red line) for each transmitter device.

Table 4.1 presents the fitting curve parameters ($RSSI(d_0)$ and η) and the distance error (difference between the estimated and Ground-Truth (GT) distance) using the moving average, RLOWESS, and moving median of the Devices 01, 03, 04, 05 and 06. The estimated distance error was expressed in terms of Root Mean Square Error (RMSE), Mean Square Error (MSE), and standard error. Moreover, for each filter and transmitter, the Sum Square Error (SSE), Rsquare, and RMSE values are provided to evaluate how well the curve fits the data.



(a) Results of the Device 01 as transmitter

(b) Results of the Device 03 as transmitter

(c) Results of the Device 04 as transmitter

(d) Results of the Device 05 as transmitter

Figure 4.2 Curve fitting based on LDPL model and distance estimation using the RSSI values, smoothed with a moving average filter, of the Subset-A (Config01) collected with the Device 02 (receiver). Source [21].

4.1.1.2 Discussion

Regarding the signal propagation in LOS, we can observe, considering the median values of the box plots, that the curves do not present a strong logarithmic attenua-

Table 4.1 Goodness of curve fit and distance errors. Source [21].

ID	Filter	RSSI(d_0)	η	Goodness of curve fit (RSSI)			Distance		
				SSE	Rsquare	RMSE	MSE	RMSE	Std. Error
	(-)	(dBm)		(dBm^2)	(-)	(dBm)	(m^2)	(m)	(-)
01	Mov. Average	-77.39	0.60	71.04	0.35	2.8	106.76	10.33	10.15
	RLOWESS	-77.48	0.59	67.32	0.35	2.73	103.65	10.18	10.13
	Mov. Median	-76.75	0.64	48.14	0.47	2.31	35.62	5.96	6.11
03	Mov. Average	-67.97	1.01	23.24	0.82	1.6	6.43	2.53	2.64
	RLOWESS	-67.49	1.05	21.68	0.84	1.55	5.7	2.38	2.49
	Mov. Median	-67.43	1.06	22.6	0.84	1.58	7.96	2.82	2.83
04	Mov. Average	-75.36	0.61	19.9	0.66	1.48	20.41	4.51	4.6
	RLOWESS	-75.21	0.61	24.91	0.61	1.66	45.26	6.72	6.83
	Mov. Median	-75.24	0.61	22.49	0.63	1.58	29.4	5.42	5.62
05	Mov. Average	-64.33	1.03	19.84	0.84	1.48	11.3	3.36	3.5
	RLOWESS	-64.45	1.01	22.1	0.83	1.56	17.77	4.21	4.4
	Mov. Median	-64.11	1.03	26.22	0.8	1.7	35.16	5.93	6.08
06	Mov. Average	-65.85	1.37	33.1	0.85	1.91	4.5	2.12	2.2
	RLOWESS	-65.86	1.37	34.99	0.84	1.97	5.16	2.27	2.36
	Mov. Median	-66	1.34	34.96	0.84	1.97	5.46	2.33	2.44

tion as the receiver moves away from the transmitter. For example, in Figure 4.1(**a**), for Device 01 (transmitter), the mean RSSI values after 5 meters started to increase rather than decrease and in Figure 4.1(**c**), for Device 04 (transmitter), the mean RSSI values after 2 meters randomly decrease and increase. Also, from the curve fitting plots in Figure 4.2 and values in Table 4.1, we can notice that the propagation of the BLE signal behaves differently depending on the transmitter device used, since the receiver and the transmission medium are identical for each of the mobile devices used as transmitters. For example, for each device transmitter (Device 01, 03, 04, 05 and 06), the RSSI at a reference distance d_0 ($RSSI(d_0)$) is on average $-77.2\,\mathrm{dBm}$,$-67.63\,\mathrm{dBm}$, $-75.27\,\mathrm{dBm}$, $-64.29\,\mathrm{dBm}$, and $-65.9\,\mathrm{dBm}$ respectively and the LDPL attenuation factor (η) is not unique even though the test was performed under similar conditions. The η values are in a range from 0.59 to 1.37.

Regarding the proper setting of the model parameters ($RSSI(d_0)$ and η) to accurately estimate the distance between transmitter and receiver, based on the results presented in Table 4.1 and Figure 4.2, we observe that the type of filter to smoothen and remove the outliers considerably affects the selection of model parameters, and in consequence, the accuracy of the estimated distance. For the three evaluated filters, the moving average filter, provides for the majority of devices a better smoothing of RSSI and a lower distance error in comparison with the other filters. Although the RMSE of the estimated distance is large, due to environmental conditions, we observe, based on Table 4.1, that some devices (i.e., Device 03, 05, and 06) present a RMSE considerably lower compared to the other devices (i.e., Devices 01 and 04). Additionally, we observe, based on Figure 4.2 (b), (c) and (d), that the distance error in the first 4 meters is small ($\approx$ 1 meter). To sum up, the BLE signals propagation indoors and in LOS conditions mainly varies depending on the transmitter device and indoor environment. So, it is impossible to provide a unique set LDPL model parameters that work for various devices and scenarios.

4.1.2 Fuzzy logic

In indoor environments, the estimation of the relative distance between the transmitter and receiver devices, based on LDPL models, is often inaccurate even under LOS conditions. Moreover, the distance estimation accuracy is highly dependent on the model used and the correct tuning of the model's parameters. Those parameters vary depending on the environment and its setting, and tuning them to provide an accurate estimation is a time-consuming task. Contrarly, after the parameters are properly set, LDPL models have demonstrated moderate accuracy in scenarios with a moderate source of degradation of radio wave propagation. Therefore, configuring a generalized set of parameters that can provide accurate distance estimation in a wide variety of indoor environments is an open challenge. In this section, we propose a fuzzy-logic based system, which relies on a RSSI-fuzzy classification of BLE signals transmitted by mobile devices to estimate distance.

The main contributions presented in this section are:

- We propose a novel and straightforward system to estimate the relative distance between two mobile devices, which rely on a RSSI-fuzzy classifier and BLE RSSI measured values.
- Our system improves the robustness and accuracy of the distance estimating process against signal variations.
- We demonstrate the system's applicability and practicality for distance estimation in indoor and outdoor scenarios.

4.1.2.1 RSSI-fuzzy classification as distance estimator

To reduce the distance estimation error due to the variability of environmental conditions, we use a system based on fuzzy logic Single Input Single Output (SISO). Fuzzy logic systems are versatile and intuitive systems, which are easy to implement and used to solve complex problems thanks to their capability to simulate human reasoning and decision-making without explicitly requiring mathematical modeling [184, 185, 186].

Figure 4.3 illustrates the SISO-Fuzzy logic system used. The system consists of the following components: the crisp input (RSSI values); the fuzzyfier, which converts the crisp input into fuzzy set values; the fuzzy inference engine, which processes the fuzzy values based on the fuzzy rules of the fuzzy rule base and provided a processed fuzzy set; the fuzzy rule base; the defuzzyfier, which converts the processed fuzzy set into crisp output; and the crisp output. A detailed description of each of these elements and their use to adjust the distance estimation in BLE–RSSI-based positioning under varying conditions is presented in the following subsections.

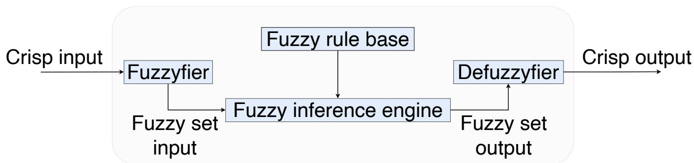


Figure 4.3 SISO fuzzy logic system.

4.1.2.2 Crisp input and output variables and membership functions

The crisp input and crisp output correspond to BLE-RSSI (dBm) values gathered by the mobile device (receiver) and the relative distance between mobile devices (transmitter and receiver) estimated by the system.

We have selected a location indoors (office scenario) and a location outdoors (parking lot), where we placed the transmitter. In both scenarios, we set 11 reference points, where the transmitter-receiver distance ranges $1\,\mathrm{m}$ to $11\,\mathrm{m}$. In these points, the RSSI values are measured. The objective is to set eleven input membership functions, which will be explained further on. The membership functions define the degree of membership of the crisp input/output values to equivalent fuzzy sets. We define the crisp outputs following the same considerations. Then, we labeled each of the eleven membership functions for input (I) and output (O) as 'I_{01}" to "I_{11}" and "O_{01}" to "O_{11}", respectively.

Regarding the membership functions, we defined their parameters and type based on the data experimentally gathered in indoors and outdoors and its statistical analysis. The type selected for the input and output membership functions are respectively trapezoidal (for labels "01" and "11") and triangular (for labels "02"–"10"). The mathematical representation of the membership function is $\mu_A : X \to [0,1]$, where A is the fuzzy set and X is the set of elements to be mapped. Eq. (4.2), which considers three parameters ($a < b < c$), mathematically expresses the triangular membership function and Eq. (4.3), which considers four parameters ($a < b < c < d$), the trapezoidal membership function.

$$\mu_{A,tgl}(x) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a \leq x < b \\ 1, & \text{if } x = b \\ \frac{c-x}{c-b}, & \text{if } b < x \leq c \\ 0, & otherwise \end{cases} \tag{4.2}$$

$$\mu_{A,trapez}(x) = \begin{cases} \frac{x-a}{b-a}, & \text{if } a \leq x < b \\ 1, & \text{if } b \leq x \leq c \\ \frac{d-x}{d-c}, & \text{if } c < x \leq d \\ 0, & otherwise \end{cases} \tag{4.3}$$

Specifically, the parameters a, b and c for Eq. (4.2) define the positions, in RSSI (dBm), of the three triangle's corners . Likewise, the parameters a, b, c, and d for Eq. (4.3) define the position of the four trapezoid's corners.

The input and output membership function values for indoor and outdoor scenarios are presented in Table 4.2 as vectors. The empirical procedure detailed in Section 4.1.2.8 was used to determine these values.

4.1.2.3 Step 1: Fuzzification

In accordance with the scheme shown in Figure 4.3, the first step is the fuzzification process. In the fuzzification process the crisp input, x (the RSSI in dBm), is mapped in membership degrees ([0,1]) for every fuzzy set (labels "01"–"11"). To this end, the membership functions ($\mu_{A,tgl}(x)$ and $\mu_{A,trapez}(x)$) expressed in eq.(4.2) and eq.(4.3) together with their parameters presented in Table 4.2 are used. As a result, we get the input fuzzy set $\mathbf{M}(x)$, which contains a vector of membership values ($\mathbf{M}(x) =$

Table 4.2 Membership function values. Source [4].

	Input Membership		Output Membership
Class	Indoor	Outdoor	Indoor/Outdoor
01	[-57,-52,-42,-41]	[-60,-54,-42,-41]	[-0.7,0,1.5,2.4]
02	[-58,-55,-52]	[-62,-60,-59]	[1.5, 2, 2.5]
03	[-57,-56,-55]	[-65,-63,-61]	[2,3,4]
04	[-64,-57,-56]	[-68,-65.5,-63]	[3,4,5]
05	[-60,-58,-56]	[-71,-69.5 -67]	[4,5,6]
06	[-65,-60,-58]	[-71,-70,-69]	[5,6,7]
07	[-69,-65,-60]	[-72.5,-72,-70.5]	[6,7,8]
08	[-68,-66,-65]	[-74,-73,-72]]	[7,8,9]
09	[-69,-68,-67]	[-75,-74,-73]	[8,9,10]
10	[-76,-69,-68]	[-74.5,-74,-73.5]	[9,10,11]
11	[-80.8,-80.2,-71,-70]	[-80.8,-80.2,-75,-74.5]	[11,12,13,20]

$[\mu_{I_{01}}(x), ..., \mu_{I_{11}}(x)])$.

4.1.2.4 Step 2: Fuzzy rules application

The Mamdani method [187] performs fuzzy logic reasoning in our system. It evaluates the rules in the fuzzy rule base as well as the fuzzy set input, which is obtained from a crisp input using the fuzzification process described in Section 4.1.2.3, to come up with the fuzzy set output. During the evaluation, the fuzzy implication operator (min) is used, and each rule is applied to each element of the input fuzzy set to get the respective fuzzy set outputs, each of which represents the output membership degrees (as determined by a specific rule) based on the input fuzzy set.

For each of the eleven reference distances, the following fuzzy rule is specified (i.e., eleven rules in total): *the input membership degree to a reference distance is used to calculate the area falling below that degree in the corresponding output membership function*. Figure 4.4 presents a graphic rule example using reference distance “01”.

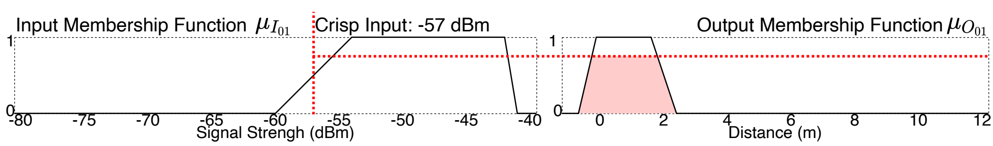


Figure 4.4 Graphical representation of the fuzzy rule for the class “01”. Source [4].

The outputs from each rule are then combined into a single, visually displayed fuzzy set output using the fuzzy aggregation operator (max).

4.1.2.5 Step 3: Defuzzification

The defuzzification process is the final step of the fuzzy logic system. After applying the fuzzy rules and finishing the fuzzy implication and aggregation operations, the crisp output (final distance estimate) is computed by applying the center of gravity to the resulting area.

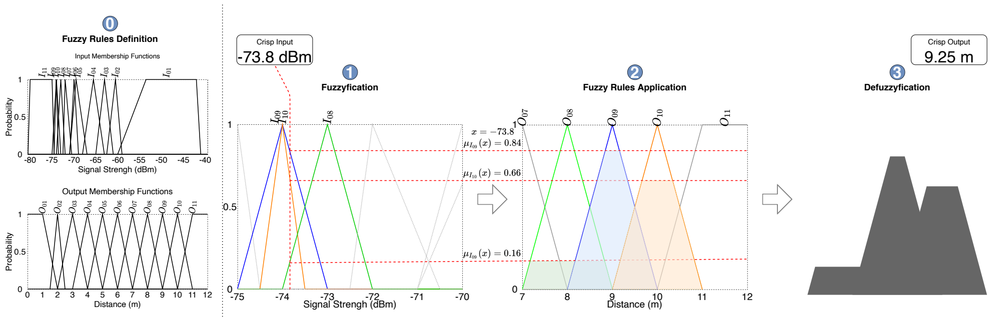


Figure 4.5 Example of a RSSI-Fuzzy classification approach to estimate distance in the outdoor scenario. Given the eleven input/output fuzzy membership functions, it shows the workflow from the crisp input, $-73.8\,\mathrm{dBm}$, to the estimated distance of $9.25\,\mathrm{m}$. Source [4].

4.1.2.6 Full example of the distance estimator based on the RSSI-fuzzy classification

The example presented in this section aims to exemplify the computation process carried out by the proposed distance estimator based on the RSSI-fuzzy classification and to explain and describe the operation of the systems and its main components, respectively. The input and output membership functions (see Section 4.1.2.2), along with their parameters, are the unique requirements that must be established to use the proposed RSSI-fuzzy classification. Table 4.2 contains the parameter values for both, indoor and outdoor scenarios used in this evaluation, and in Section 4.1.2.8 the empirical procedure to obtain the parameters is explained to guarantee reproducibility. The versatility of our proposed system allows us to apply it to a new environment and hardware setup, only updating the parameters of the membership functions considering the statistical distribution (box plots) of the new RSSI values at different reference distances.

The crisp input in our case is the RSSI value of $-73.8\,\mathrm{dBm}$, which corresponds to the average of the RSSI values gathered in the reference point located at $9\,\mathrm{m}$. It should be noted that RSSI are typically integer values. However, computations as the average to reduce noise levels may produce decimal RSSI values.

The first step corresponds to the fuzzification, which maps the crisp input value (RSSI value) using the eleven input membership functions (see Figure 4.5 step 1) to get the input fuzzy set $\mathrm{M}(x)$. In our case, only three membership functions ($\mu_{I_{08}}$ (green), $\mu_{I_{09}}$ (blue), and $\mu_{I_{10}}$ (orange)) presented non-zero input membership probabilities. $\mu_{I_{09}}(-73.8)$ reported the highest probability (0.84).

The second step corresponds to the fuzzy rule application. Here, we calculate the area falling under the corresponding membership output functions based on the intersection between the $-73.8\,\mathrm{dBm}$ line and the non-zero membership input functions $-73.8\,\mathrm{dBm}$ ($\mu_{I_{08}}$, $\mu_{I_{09}}$ and $\mu_{I_{10}}$). For example, the area of O_{09} corresponds to a probability equal to or lower than 0.84, the membership degree provided by $\mu_{I_{09}}(-73.8)$.

In the last step, to create a single area, we merge the overlapping areas, and then, we compute the center of gravity to get the estimated distance. In this example is $9.25\,\mathrm{m}$. A graphical representation of the workflow of the system is presented in Figure 4.5.

4.1.2.7 Objectives and experimental setup

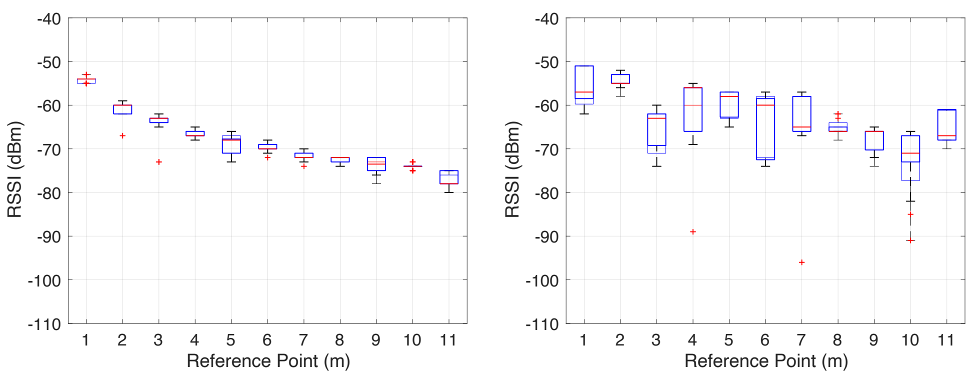
The experiments of this section aim to validate and evaluate the accuracy of the estimated distance and robustness provided by our fuzzy logic-based system in comparison with a standard LDPL model. The scenarios used to carry out the experiments correspond to a real office scenario (indoor scenario) described in Section 3.2.2 and depicted in Figure 3.3 and a parking lot (outdoor scenario). In each scenario, two smartphones were located face to face in LOS –one of them transmitting and the other receiving iBeacon messages– at distance intervals of $1\,\mathrm{m}$ from $1\,\mathrm{m}$ to $11\,\mathrm{m}$. In order to apply our proposed approach and the traditional LDPL model baseline, we use the data collected in the indoor scenario (office data[1]) and the outdoor scenario (parking lot data[2]). The office and parking lot data sets include 427 and 656 samples, respectively. The corresponding data sets, which include both indoor and outdoor environments, are available as supplementary materials in [188]. We divide both data

[1]file: `Set01_Config01_Honor_office_portrait_090.csv`
[2]file: `Set01_Config01_Honor_parking_portrait_090.csv`

sets into two subsets (training (70%) and testing (30%)). We applied a moving average filter in the training subset to process outlier RSSI values and remove samples higher than 3 times the Median Absolute Deviation (MAD) method for the testing subset.

4.1.2.8 Empirical setting of RSSI–fuzzy system

The input and output membership functions parameters (see Table 4.2) used in our proposed RSSI–fuzzy classification are specified in two phases. The first phase uses box-plots (see Figure 4.6(**a**) and Figure 4.6(**b**)) to provide the statistical information at every reference distance (from 1 m to 11 m). The values of the input triangular membership functions ([a,b,c]) are determined by the first, second (median), and third quartiles. For the trapezoidal input membership functions, the values for [a,d] are given by the first and third quartiles. The value for c (class *"01"*) and b (class *"11"*) are given by the second quartile (median). The remaining values –b (class *"01"*) & c (class *"11"*)– are set to guarantee the trapezoids symmetry.



(a) Outdoor scenario (Parking lot) **(b)** Indoor scenario (Office)

Figure 4.6 Box plots of train subset (outdoor and indoor scenarios). Source [4].

We equally distribute the parameters for the output membership functions throughout the $[1, \ldots, 11]$ range. We set the highest membership degrees at the eleven reference distances, and the width of the functions is set to 2 (i.e., $c - a = 2$ and $d - a = 2$). In the second phase, we manually fine-adjusted the input and output membership function parameters set in the first phase by comparing the output to the expected reference value and checking the input values corresponding to the median, first and second quartile. The membership function was manually moved or even skewed to its center value in the event of a significant amount of overlap between the membership functions and/or a significant error in the distance.

Finally, the output membership functions of fuzzy sets (*"01"* & *"02"*) and (*"10"* & *"11"*) were re-tuned (changes on vertex angles/small horizontal function shift) to avoid large errors near the distance range boundaries due to the increase/attenuation of the RSSI in short and large distances between transmitter and receiver.

The output membership functions are the same for indoor and outdoor scenarios, as the locations for the reference points kept the same distances between the emitter and the receiver.

4.1.2.9 Setting of traditional LDPL model

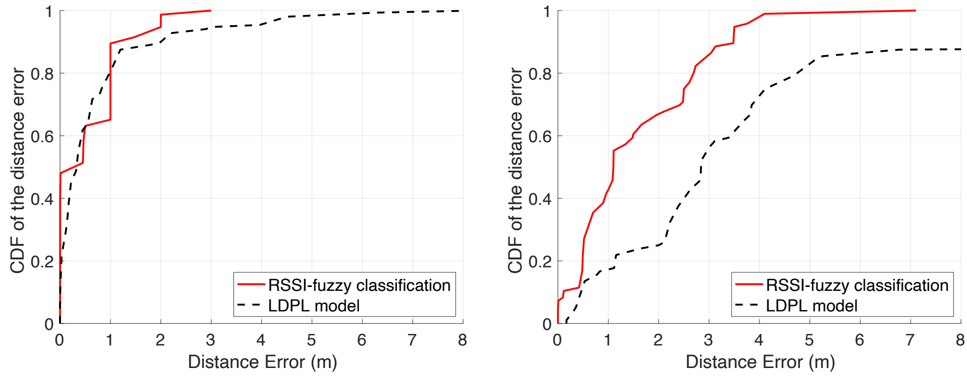
To compare our proposed system, we used a standard LDPL model to estimate the distance, which is described in detail in Section 4.1.1 and mathematically expressed in the Eq. 4.1.

The setting of the parameter values $RSSI(d_0)$ and η were computed based on the non-linear least squares method considering the data of the training subsets. The η value for the outdoor and indoor scenarios are 2.1 and 1.2 respectively, and the $RSSI(d_0)$ value is $-53\,\mathrm{dBm}$ for both scenarios.

4.1.2.10 Results

For the two analyzed models (RSSI–fuzzy classification and LDPL) in indoor and outdoor scenarios, we have evaluated their accuracy considering the absolute error of the distance estimated between two mobile devices. The Empirical Cumulative Distribution Function (ECDF) plot in Figure 4.6(a) and Figure 4.6(b) present the results for outdoor and indoor scenarios, respectively. In each plot, the red line corresponds to the results of the RSSI–fuzzy classification approach and the black dashed line of the LDPL model.

Moreover, in Table 4.3, we present a detailed summary of the results in each of the eleven reference points separately and the overall results for each scenario using the RMSE values.



(a) Outdoor scenario (Parking lot) **(b)** Indoor scenario (Office)

Figure 4.7 Empirical Cumulative Distribution Function (ECDF) of the distance error (outdoor and indoor scenarios). Source [4].

Table 4.3 RMSE of the fuzzy Logic and LDPL approaches in the diverse scenarios. Source [4].

	Parking RMSE (m)		Office RMSE (m)	
Distance (m)	RSSI–fuzzy classification	LDPL model	RSSI–fuzzy classification	LDPL model
1	0.008	0.1142	2.7535	1.6045
2	0	0.1313	0.6977	0.5322
3	0.2212	0.2249	3.5779	9.9766
4	0	0.5423	2.1143	2.2062
5	1.3599	1.3906	0.6809	2.4262
6	0.8095	0.6487	1.4053	3.068
7	1.0587	1.1712	0.3861	4.3054
8	1.0003	0.2014	0.6003	3.8444
8	2.0003	0.5008	1.1887	17.9901
10	0.5008	0.3191	1.9755	14.2319
11	0	4.007	3.2986	4.4846
Average over 1-11	0.854	1.3474	2.0443	8.1543

4.1.2.11 Discussion

The box plots in Figure 4.6(a) and Figure 4.6(b) show the propagation BLE signal through the RSSI values, measured at each reference point, in the outdoor and indoor scenarios, respectively. Analyzing the outdoor scenario (the parking lot), we can notice, through Figure 4.6(a), a smaller dispersion in the distribution of the data collected at each reference point, which indicates a low fluctuation as the BLE signals propagate. In addition, the signals follow an evident logarithmic attenuation pattern as they propagate in the environment, as is to be expected in the outdoor environments with LOS conditions. Considering the ECDF (Figure 4.7(a)) and RMSE values (Table 4.3), we visually observe that our proposed fuzzy-logic based system presents a large area of practically zero error, and in comparison with LDPL model results, our approach performs better than the LDPL model approach, except in a few cases.

Unlike the behavior of the signals of BLE in the outdoor scenario, the signals of BLE in the indoor scenario (the office) present a greater fluctuation, as it can be seen in Figure 4.6(**b**). In addition, the BLE signals do not exhibit a clear logarithmic attenuation behavior as they move away from the mobile device transmitter. Despite the uncertainty of RSSI values, the empirical results shown in Figure 4.7(**b**) and Table 4.3 demonstrated that our proposed Fuzzy-RSSI approach not only enhances the LDPL model's overall accuracy (RMSE), but it also minimizes the large values of error present in the distance estimate. The error of the distances estimated by our fuzzy-logic based system is on average four times lower than LDPL model.

The proposed fuzzy-logic based system minimizes the presence of significant errors in estimating relative distances in both scenarios (indoor and outdoor), demonstrating the robustness of our approach. In addition, the range of the distances for the fuzzy-logic based system is $[-0.7, \ldots, 20]$, but the LDPL model does not provide limits for the estimated distances and it is hence more vulnerable to severe outliers.

4.2 Position estimation

There is a growing interest in improving the accuracy of mobile/wearable device position estimation using Wi-Fi and BLE technologies. Within the methods implemented based on such technologies, the most common are RSSI-lateration and fingerprinting–k-NN due to their easy implementation, capability to use the technologies and measurements on mobile/wearable devices, and acceptable accuracy [180]. Despite the advantages of RSSI-lateration and fingerprinting–k-NN, they present some positioning accuracy decrements due to the anchors and the set of parameters used in the estimation of the position, and the environmental conditions.

In this section, we explain the operational principle and the sources of positioning errors of the conventional RSSI-lateration and fingerprinting–k-NN methods, which are used as the baseline in our proposed collaborative indoor positioning presented in Chapter 5. Based on the premise that not all anchors deployed contribute positively to improving the positioning accuracy, we propose a lateration BLE–RSSI method based on combinatorial anchors selection. This method selects suitable anchors to enhance the accuracy and reliability of the position estimation. Also, we introduce a fingerprinting–k-NN method based on BLE and analyze the effect of the number of samples and k values on positioning accuracy.

4.2.1 Lateration and anchors selection

One of the most common methods for IPSs is lateration [189, 6]. Lateration uses the GT position of anchors present in the indoor environment, at least 3 anchors as references, and the relative distance (measured or estimated) between them and the unknown target [6, 48]. As it was stated in the section about distance estimation (Section 4.1), among the diverse techniques to estimate distance, the RSSI-based techniques are widely used in mobile/wearable devices. In addition, the wide availability and energy efficiency of BLE technology embedded in mobile/wearable devices, and its increasing deployment in indoor environments, makes lateration approaches, based on BLE–RSSI, popular in IPSs.

The positioning accuracy for those IPSs using lateration with BLE-RSSI is mostly determined by two factors: first, the adequate distribution (density and geometric position) of chosen BLE anchors; and second, the accurate distance estimation between the unknown target and reference BLE anchors [190, 4, 191]. Consequently, those are its two main sources of positioning inaccuracy.

Although in ideal conditions, a greater number of BLE anchors can enhance position estimation, in real scenarios, this is not always feasible, and furthermore, some (additional) anchors may not provide an accurate distance estimation that positively contributes to enhancing the positioning accuracy [79]. Thus, different levels of positioning accuracy of the same target can be reached depending on the group of BLE anchors selected. So, the reliability and positioning accuracy of lateration approaches can be improved by adding a method capable of exploiting the availability and geometric distribution of BLE anchors and effectively selecting them. On the one hand, in outdoors, the anchors' selection problem and the analysis of their geometric distribution have been widely addressed [192, 193, 194]. On the other hand, in indoors it remains as an open issue. The few existing approaches are based on variations of Cramér Rao Lower Bound (CRLB) [79], Geometric Dilution of Precision (GDOP) [195, 194], and MSE [196], which are mainly applied to Ultra-wide band (UWB) and Wi-Fi. However, such solutions have not yet been proposed for BLE.

In this section, we present a BLE–RSSI lateration method based on combinatorial BLE anchors selection to enhance the positioning accuracy, which relies on the geometrical analysis of BLE anchors and combinatorial positional estimation. Moreover, we evaluate and experimentally demonstrate, in a real indoor scenario, its usefulness in increasing positioning accuracy. The main contributions are:

- We propose a novel BLE–RSSI lateration method based on combinatorial BLE anchor selection.
- Our method enhances the accuracy and reliability of the position estimation thanks to a suitable BLE anchor selection, which is based on a geometrical analysis of BLE anchors and combinatorial positional estimation.
- We demonstrate the usefulness of BLE anchor selection to increase positioning accuracy experimentally in a real indoor environment.

4.2.1.1 Lateration BLE-RSSI based indoor positioning system

Lateration BLE-RSSI method computes the target position based on the distance between the target and M BLE reference anchors and the GT coordinates of the anchors [191, 197]. The computation is performed in two sequential steps. The first step, which estimates the relative distance based on the relationship between BLE RSSI and the distance between transmitter and receiver, is computed. In our specific case, by the LDPL model described in Section 4.1 and expressed in the Eq. 4.1. The second step, based on the estimated distances (BLE anchors-target), computes the target position considering it as an optimization problem, which is solved using the least squares method [197, 198]. Specifically, we consider the Levenberg-Marquardt algorithm for nonlinear least squares. The lateration method is represented as a minimization of the sum of squared errors between the measured distances (d_m) and hypothetical ones ($g_m(\underline{\mathrm{x}})$), which is denoted by Eq. (4.4) and $g_m(\underline{\mathrm{x}})$, the unknown target position, by Eq. (4.5) [199].

$$\min_{\underline{\mathrm{x}}} \sum_{m=1}^{M} \left(g_m(\underline{\mathrm{x}}) - d_m\right)^2 \tag{4.4}$$

$$g_m(\underline{\mathrm{x}}) \triangleq \sqrt{(x - bx_m)^2 - \left(y - by_m\right)^2} \tag{4.5}$$

$m = \{1, 2 \ldots M\}$ denotes the number of BLE reference anchors; $\underline{\mathrm{x}} = \{x, y\}$ denotes the unknown coordinates of the target; and $\{bx_m, by_m\}$ the GT coordinates of BLE reference anchors.

4.2.2 Proposed lateration based on effective combinatorial BLE anchors selection

The goal of our proposed BLE anchors selection is to enhance the reliability and accuracy of the target position estimated by the IPS. To this aim, we estimate diverse positions, of the same target, considering different combinations of surrounding BLE reference anchors and the geometric analysis of each of them.

For the sake of clarity, first, we explain the methodology of our approach, which consists of four phases, and then its practical implementation in nine steps.

The first phase aims to gather all the detectable BLE anchors and summarize their RSSI values. To do this, the nearby BLE anchors detected by the target mobile device, within 1 minute, are categorized according to their minor and major values (BLE anchors unique identifiers). Consequently, each BLE anchor has a unique set of RSSI values. Then, the RSSI outliers of each BLE anchor set are removed, considering three scaled MAD from the median, and the remaining RSSI values of each set are averaged. Finally, each BLE anchor set (called initial BLE anchor set) contains a unique RSSI value for every anchor detected by the target. We apply two considerations when building the initial BLE anchor set: first, to guarantee a reliable lateration, we just include anchors with an average RSSI values $\geq -83\,\mathrm{dBm}$ as a threshold, which correspond to the range of usable signal strength in BLE (nearest anchors) for our scenario. The value was defined experimentally; and second, due to computational feasibility, we only include a maximum of 9 anchors, those with the strongest RSSI values.

The second phase aims to combinatorially group the detected BLE anchors and estimate the position of each group. Our analysis is based on subsets of 5 anchors to keep a trade-off between the number of anchors used in the lateration with the number of combinations to be explored (126 combinations according to Eq. (4.6)) and to avoid a heavy computational load. The value of n=5 allows us to test the maximum number of combinations possible (126), which is needed in our approach focused on combinations to determine the best-estimated position. Larger numbers enhance the probability of incorporating data from anchors with significant Non-line-of-sight (NLOS) components, but smaller numbers would be within the bottom boundaries for 2d and 3d lateration. The lateration method is used to get a single position estimated ($\hat{p} = [\hat{p}_x, \hat{p}_y]$) for each combination of 5 anchors. Eq. 4.6 is used to compute the number of combinations.

$$\binom{n}{K} = \frac{n!}{K!\,(n-K)!}, \quad for \quad 0 \leq K \leq n \tag{4.6}$$

Where n denotes the number of anchors in the reduced subsets and K is the total number in the pool of available BLE anchors. As mentioned above, $K = 9$ and $n = 5$. The third phase aims to determine the accuracy deviation of the estimated target position based on a triangulation approach. To this aim, for each of the subsets with 5 anchors, the following steps are performed:

- Triangulation: we consider two types of triangles: the first, the area–estimated triangle (green triangles in Figure 4.8), with two of its vertices corresponding to two reference points and the third one to the estimated target position ($\hat{p} = [\hat{p}_x, \hat{p}_y]$) computed in phase 2; and the second, the area–target triangle (blue triangles in Figure 4.8, with two of its vertices corresponding to two reference points and the third one to the (virtual) target position ($p = [p_x, p_y]$). The (virtual) target position is estimated by a lateration method that uses the K anchors used to create the combinations. In our case, $K = 9$. Figure 4.8 exemplify both types of triangles (4 each) for a concrete combination of 5 BLE reference points (b_1, b_2, b_3, b_4, b_5).

- Compute pair-wise accuracy deviation: after the triangles have been defined, a pair-wise difference, based on vertices of the same BLE reference point, is conducted between the areas of the area-target (blue - A) and the area–estimated (green - $\hat{A}$) triangles to get a single accuracy deviation of the estimated position. The triangle areas are calculated by Eq. (4.7) and Eq. (4.8) and the difference between triangles by Eq. (4.9). It should be noted that the difference tends to zero when the estimated position gets closer to the actual position ($\hat{p} \approx p$).

- Compute overall accuracy deviation: finally, we sum every pair-wise individual degree of error obtained from the previous step to get an overall accuracy deviation.

$$A_m = \frac{1}{4}\sqrt{4a_m^2 a_{m+1}^2 - \left(a_m^2 + a_{m+1}^2 - c_m^2\right)^2} \tag{4.7}$$

$$\hat{A}_m = \frac{1}{4}\sqrt{4\hat{a}_m^2\hat{a}_{m+1}^2 - \left(\hat{a}_m^2 + \hat{a}_{m+1}^2 - c_m^2\right)^2} \tag{4.8}$$

$$Ac_{dev}(Set) = \sum_{m=1}^{M-1} \mid A_m - \hat{A}_m \mid \tag{4.9}$$

where Ac_{dev} is the accuracy deviation of the Set under evaluation; M is the number of BLE reference anchors contained in the Set under evaluation; A_m the area-target triangle of the m pair-wise triangle; a_m and a_{m+1} the first and second edge of the A_m triangle; $\hat{A}_m$ the area-estimated triangle of the of the m pair-wise triangle; $\hat{a}_m$ and $\hat{a}_{m+1}$ the first and second edge of the $\hat{A}_m$ triangle, and c_m the common edge of the triangles A_m and $\hat{A}_m$.

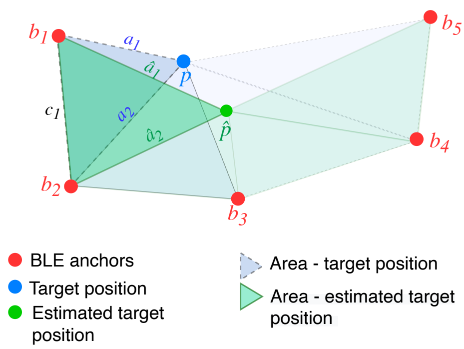


Figure 4.8 Example of triangle areas used in the pair-wise accuracy deviation calculation to evaluate the accuracy of estimated target position ($\hat{p}$), estimated considering the BLE reference anchors set ($\{b_1, b_2, b_3, b_4, b_5\}$). Source [6].

The final phase aims to select the combination of 5 BLE reference anchors that provide the best accuracy. To this end, the results from phase 3, accuracy deviation, are sorted in ascending order and the combination with the lowest accuracy deviation is selected. The selected combination is considered to have the best individual accuracy, and our method provides its estimated position as the final estimated position.

The practical implementation of our proposed methodological approach is presented in Algorithm 1, and its workflow is summarized as follows:

- **1st step:** Gather the RSSI from from surrounding BLE anchors during 60 s excluding those not belonging to the reference anchor set Algorithm 1);

- **2nd step:** Categorize the RSSI values by anchor removing outlier values. An outlier is considered as a value falling out of 3 times the scaled MAD from the median (lines 1–2 in Algorithm 1);

- **3rd step:** Average the RSSI values of each reference anchor to obtain a single averaged RSSI value per reference anchor (line 3 in Algorithm 1);

- **4rd step:** Select the reference BLE anchors with averaged RSSI equal or greater than $-83\,\mathrm{dBm}$ (lines 4–8 in Algorithm 1), and in case of more than 9 anchors, just consider the 9 strongest ones (lines 9-11 in Algorithm 1);

- **5th step:** Estimate the relative distances of selected reference BLE anchors to the target position, using the LDPL model (expressed by eq.(4.1)), and their RSSI values (line 12 in Algorithm 1). We considered the path-loss attenuation factor (η) of 2.1 and the $RSSI(d_0)$ equal to $-63.78\,\mathrm{dBm}$ (input values in Algorithm 1), which were defined experimentally for our scenario;

- **6th step:** For the set of the 9 selected reference anchors selected in the previous steps, create $\binom{5}{9} = 126$ combinations (without repetitions) of 5 reference anchors (line 13 in Algorithm 1);

- **7th step:** Estimate the target position for each combination created, using the Levenberg-Marquardt Least Squares (L-MLS) lateration method to fit the euclidean distance model. We get one estimated target position per combination (line 15 in Algorithm 1). The input data to fit the model are the distances estimated in the fifth step, and the weights and the GT of the BLE anchors corresponding to each subset. The weight value for every BLE anchor is computed as the inverse of its distance square with respect to the target;

- **8th step:** We evaluate the appropriateness of the estimated target position of each of the 126 combinations using the difference of triangles approach defined by Eq. (4.9) and supported by the triangle areas provided in Eq. (4.7) and Eq. (4.8) (line 16 in Algorithm 1), and

- **9th step:** The combination reporting the lowest difference of the triangle approach is selected and its estimated position is set as the final estimated position (line 18 in Algorithm 1).

Algorithm 1 Estimation of Target Position

```
Input: Deployed anchors information
Input: RSSI values
Input: LDPL: η = 2.1 and RSSat1m = −63.7816 dBm
Input: threshold = −83 dBm
Output: estimated position
Group the RSSI values by anchor
Remove RSSI outliers of each group
Average RSSI values of each group: RSSI(i) (overlined)
for i ← 1 to number of RSSI(i) do
    if (RSSI(i) ≥ threshold) then
        Include i-th anchor to reference anchors set (ref_BLEset)
    end if
end for
if (length(ref_BLEset) ≥ 9) then
    Sort ref_BLEset according to the corresponding RSSI values in descending order and remove those anchors
    above the 9th position (e.g., 10th, 11th, ...)
end if
Estimate the relative distance between anchors of ref_BLEset and the target position using eq.(5.1), with values
η and RSSat1m
Create (5 over 9) = 126 combinations without repetition. Where 9 represents the anchors in ref_BLEset and 5 is the
number of reference anchors per combination
for j ← 1 to 126 do
    Estimate the target position with the combination (j) using the Levenberg-Marquardt Least Squares (L-
    MLS) lateration method
    Evaluate the target position estimated considering the anchors used in combination (j) and using the dif-
    ference of triangle approach defined by Eq. (4.9).
end for
Select the estimated position considering the combination with the lowest difference of triangle approach value.
```

4.2.2.1 Experimental evaluation

The empirical experiments aim to demonstrate the usefulness of our proposed BLE anchor selection method to reduce the positioning error and to validate the positioning accuracy of our method with respect to the traditional lateration baseline. To these aims, we estimate the position of each reference point (target point) with both approaches, our proposed method and a traditional nearest node lateration strategy, which is widely used in IPSs.

The experimental scenario corresponds to the office scenario introduced in Section 3.2.2 and shown in Figure 3.3(**b**). The scenario contains 20 BLE anchors deployed in the office (red circles depicted in Figure 3.12(**b**)) and 13 target points (blue circles depicted in Figure 3.12(**b**)). Table 3.8 presents their GT coordinates.

We conduct the BLE RSSI data collection for 10 minutes in each reference point using a mobile device (Samsung A5). However, in the traditional and our proposed method, we used 10 non-overlapping intervals of 1 minute at each test point.

The relative distance estimation, using lateration, is computed based on the LDPL model. For our specific scenario, we empirically defined its parameters as 2.1 and $-63.7816\,\mathrm{dBm}$ for the path-loss attenuation factor and $RSSI$ at 1 m, respectively. Additional details are provided in Section 3.5.3.1.

4.2.2.2 Results

The principal positioning results for our proposed method (Prop.), the traditional nearest node lateration method (Trad.), and an ensemble approach (Trad. + Prop.), which combines the estimated positions from both methods, are presented in Table 4.4. Additionally, the percentage of the error differences between the traditional (Trad.) with respect to our methods and the ensemble approach is presented.

Table 4.4 Main results metrics provided by the traditional lateration, our proposed approach, and an ensemble model. Source [6].

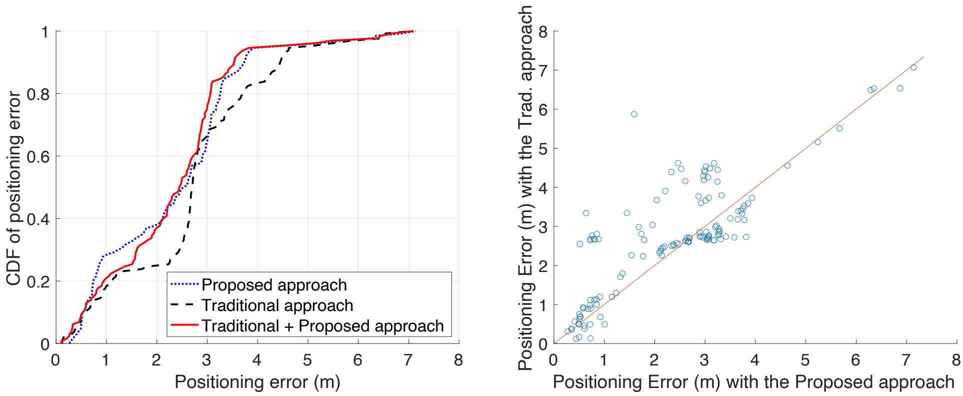
	Trad.	Prop.		Trad. + Prop.	
Eval. metric	Error (m)	Error (m)	Diff.	Error (m)	Diff.
RMSE	3.07	2.74	↓10.75%	2.68	↓12.70%
Average	2.71	2.34	↓13.65%	2.33	↓14.02%
Median	2.71	2.57	↓ 5.16%	2.46	↓ 9.23%
75th percentile	3.46	3.18	↓ 8.09%	3.01	↓13.01%
90th percentile	4.46	3.74	↓16.14%	3.54	↓20.63%

We present in Figure 4.9(**a**) the ECDF positioning error plots of our proposed method (blue dotted line), traditional method (black dashed line), and the ensemble approach (red line). Moreover, we present a general view of the point-by-point positioning errors of our proposed method and the traditional one in Figure 4.9(**b**).

4.2.2.3 Discussion

According to the results reported in Table 4.4, our proposed method performs better than the traditional lateration, with between 5% (median) and 16% (90 percentile). However, analyzing the errors one by one using the ECDF (see Figure 4.9(**a**)), we observe that in a few cases our method provides worse results than the traditional lateration.

Figure 4.9(**b**) provides an overview of the individual positioning errors of both the proposed and traditional methods. As it can be deduced, the proposed method



(a) ECDF plot of the three approaches

(b) Comparison of individual errors provided by the traditional lateration and the proposed method

Figure 4.9 Result of the traditional lateration, our proposed method, and the ensemble approach. Source [6].

provides better results than the traditional method in the majority of the cases (points above the red diagonal) – being much better in some of them – whereas the traditional method is only better than the proposed method in a few cases (points under the red diagonal).

As a way to minimize this effect, we decided to combine the estimated positions provided by the traditional lateration and our proposed method with a simple point average. As a result, the ensemble approach (combining the traditional and proposed methods) provided even better results compared to the proposed method (see Table 4.4) and is the best overall approach, generally beating any of the individual methods.

4.2.3 Fingerprinting

Fingerprinting-based positioning systems are widely used, mainly because they can exploit wireless signals previously designed for other purposes (opportunistic signals) and, under favorable conditions, provide positioning accuracies around 2.5 m. A scheme that exemplifies the operational principle of systems based on fingerprinting is illustrated in Fig. 4.10. The scheme describes an indoor environment, which contains m Access Points (APs) ($[Ap_1, \ldots, Ap_m]$) and n reference points marked on the floor ($[P_1, \ldots, P_n]^T = [(X_1, Y_1), \ldots (X_n, Y_n)]^T$). The aim of the fingerprinting positioning approach is to estimate the unknown position of device D1 ($(?_x, ?_y)_{D1}$).

The fingerprinting approach consists of two phases, a preliminary phase (training phase) and an operational phase.

In the preliminary phase (indicated in blue in Fig. 4.10), a data collection campaign is performed to save the m RSSI values of the APs in each n reference point. For example, for reference point P_1, corresponding to $[X_1, Y_1]$ (purple pin on the upper left corner in Fig. 4.10), we save the row $[RSSI_{1,1} \dots RSSI_{1,m}]$. In case an AP is not heard, a default bogus value –for instance, a very low RSSI value such as $-150\,\mathrm{dBm}$– is stored instead. This step may be performed one or multiple times on the reference point, resulting in one or multiple fingerprints per reference point. A similar procedure is performed for each reference point to create a fingerprinting radio map, which contains a matrix with the coordinates of each reference point and its corresponding RSSI values.

In the operational phase (indicated in green in Fig. 4.10), the device D1 collects the RSSI values (i.e., $[RSSI_1 \dots RSSI_m]$) of the APs. Similarly to the training phase, In case an AP is not heard, a default bogus value is used instead. Then a matching algorithm (e.g., k-NN) compares the RSSI row of D1 with those stored in the radio map to estimate the position of device D1 ($(\hat{P}_x^{FP}, \hat{P}_y^{FP})_{(D1)}$). A matching algorithm based on k-NN will be explained further on.

It should be noted that the number and order of the elements of the rows (database and operational phase) corresponding to the m RSSI values of APs must be preserved to perform the comparison between them.

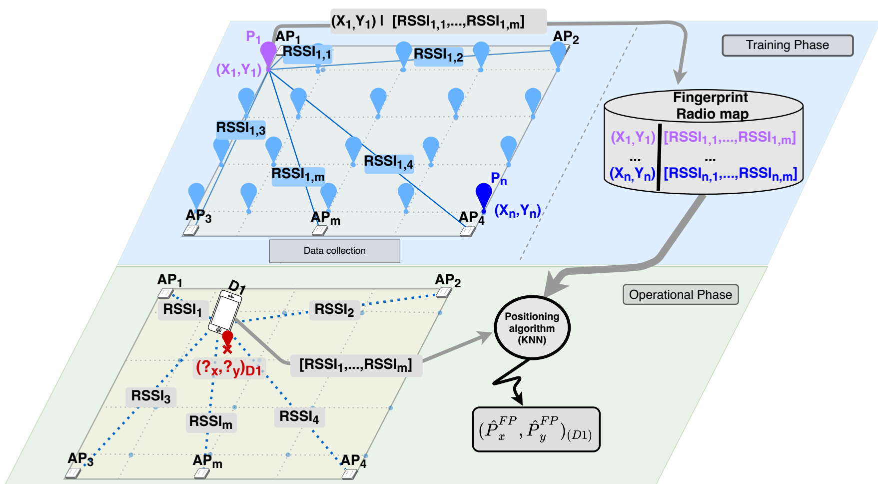


Figure 4.10 Fingerprinting-based positioning system scheme.

Regarding the matching algorithm, k-NN is the most used due to its easy implementation and its few parameters (i.e., k value and a distance metric) [200].

Fig. 4.11 graphically explains, in 4 steps, the k-NN algorithm. In the first step, the algorithm computes the distance, using the euclidean distance, between the row of RSSI values collected in the unknown position of the device D1 (i.e., $[RSSI_1 \ldots RSSI_m]$) and each of the rows of the fingerprinting radio map. As a result, a vector is obtained with the distances of each row of the fingerprinting radio map that corresponds to the vector of coordinates where they were collected. Second, the elements of the distance vector are sorted in ascending order, which also applies to their respectively coordinates vectors; in the third step, the elements of the vector are selected accordance with the k value; and in the last step, the centroid is applied to the corresponding coordinates to get the estimated position $((\hat{P}_x^{FP}, \hat{P}_y^{FP})_{(D1)})$.

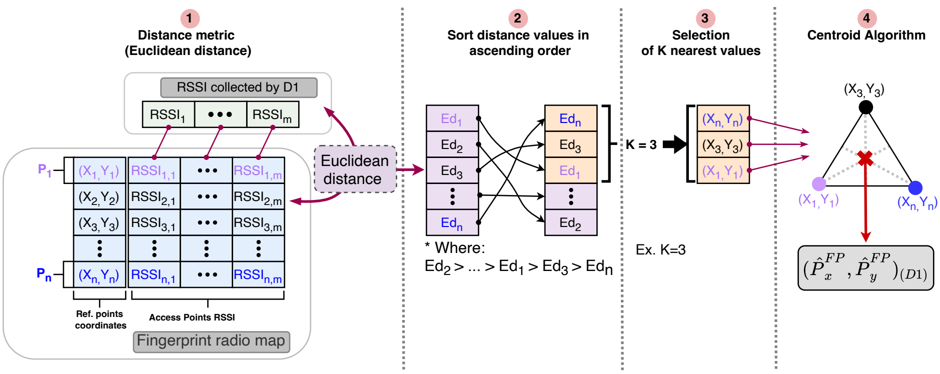


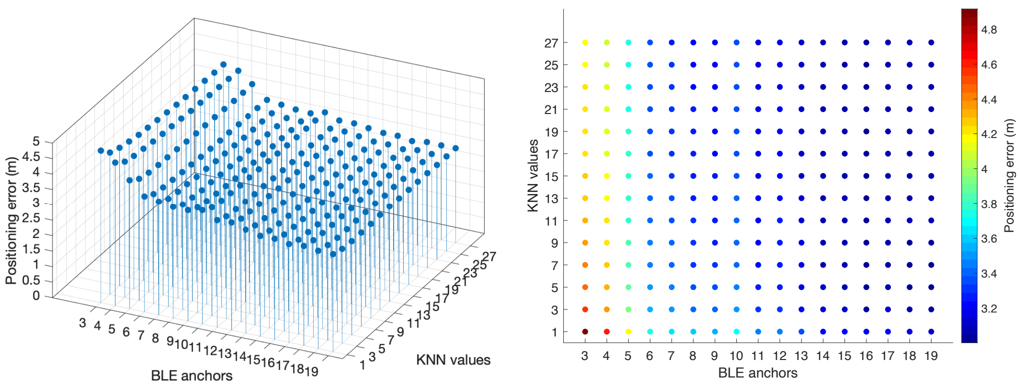
Figure 4.11 k-NN matching algorithm scheme.

4.2.3.1 Experiments and results

The scenario used for the training and operational phase of the fingerprinting–k-NN method based on BLE technology is the office scenario described in Section 3.5.3.1 and sketched in Figure 3.12(a). The scenario contains 19 BLE anchors deployed in the office (red circles depicted in Figure 3.12(a)) and 74 reference points (blue circles depicted in Figure 3.12(a)) used to create the radio map. The radio map contains 962 samples, 13 per reference point. The sample values correspond to the RSSI values from the 19 BLE anchors deployed in the environment. The operational phase estimated the position of the devices in the seven configurations depicted in Figure 3.4 and Figure 3.5.

We performed two experiments. Experiment one estimates the positioning of the devices based on the fingerprinting–k-NN method and considers two aspects: different odd values of k (i.e., 1, 3,...,27) and subsets of the 19 BLE deployed anchors. Specifically, we create 16 subsets that combine 3,...,19 BLE anchors, respectively. Each subset includes ten random combinations of each (i.e., 10 subsets of 3, 10 subsets of 4, etc.). Due to the variation in the number of BLE anchors considered, the dimension of the radio map also varies. In experiment two, the value of k ($k = 5$) is fixed, and instead of including only ten random combinations, we include all the possible combinations in each subset. The combinations are performed considering all the 19 available anchors deployed. The number of combinations for each BLE anchor subset is shown in Figure 4.13(**a**). The k value was selected based on the positioning accuracy results of experiment one and to reduce the computational load.

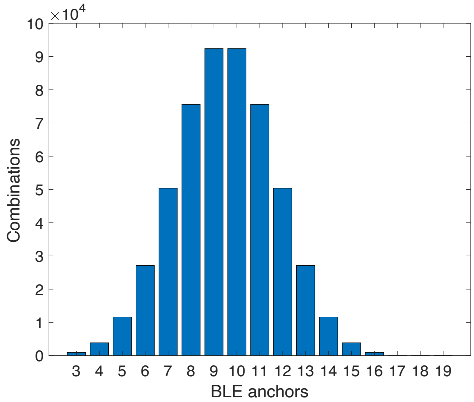
Figure 4.12 presents the results of the experiment one. In Figure 4.12(**a**) the x-axis, y-axis, and z-axis indicate the number of BLE anchors selected from the 19 BLE anchors in each subset, the value of k used in the k-NN algorithm, and the positioning error, respectively. Similarly, in Figure 4.12(**b**), except that the positioning error is represented with a bar color.



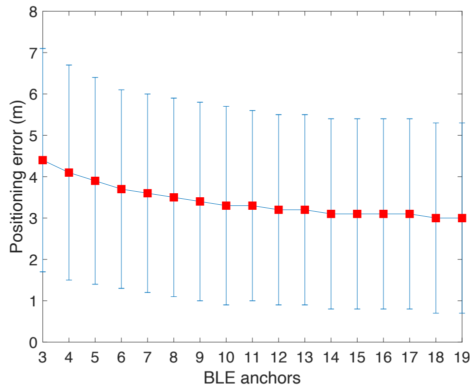
(a) 3D plot **(b)** Scatter plot

Figure 4.12 Positioning error of fingerprinting using different BLE anchors and K values.

Figure 4.13(**b**) presents the result of experiment two. The x-axis indicates the number of BLE anchors selected from the 19 BLE anchors in each subset, and the y-axis indicates the positioning error.



(a) BLE anchors combinations



(b) BLE anchors VS positioning error, with$k = 5$

Figure 4.13 Number of combinations of BLE anchors and positioning error of fingerprinting–k-NN using different BLE anchors and $k = 5$.

4.2.3.2 Discussion

Fingerprinting approaches consider three important elements to estimate the position. One is the radio map, which collects the RSSI information in diverse reference points from the surrounding APs or anchors. The second is the matching algorithm, in our case, the k-NN algorithm, whose performance depends on the value of k, and the third is the data gathered in the operational phase. Our experiments explored the effect of the number of BLE anchors used to build the radio map and the values of k on positioning accuracy.

As it can be noticed in Figure 4.12, the positioning error is different in each combination of BLE anchor and k value used. In detail, the number of BLE anchors impacts the positioning accuracy more than the values of k selected (see Figure 4.12(b)). Similarly to the results plotted in Figure 4.12 regarding the number of BLE anchors, in Figure 4.13(b), we can observe the reduction of positioning error as the number of BLE anchors increases. Specifically, the mean positioning error with 19 BLE anchors is 3 meters, and with all possible combinations of 3 anchors, it is 4.4 meters.

To sum up, we observe that a low number of BLE anchors (i.e., below ten BLE anchors) decrements the positioning accuracy considerably in fingerprinting–k-NN. Moreover, for positioning accuracy, an increased value of k is less important than the increase of the number of BLE anchors. Although there is no method to choose the most suitable value of k, based on our results the lowest values of k (i.e., 5 to 11) when there are at least 5 anchors present a good result.

4.3 Chapter summary and discussion

In this chapter, we described and experimentally evaluated the traditional methods to estimate distance (i.e., based on LDPL model and fuzzy logic) and position (i.e., RSSI-lateration and fingerprinting–k-NN), which allowed us to identify their limitations and challenges.

The importance of studying the previous approaches is for their use in developing the algorithms used in our CIPSs and in the traditional IPS presented in Chapter 5. Additionally, we proposed an innovative lateration BLE-RSSI method to enhance the accuracy and reliability of position estimation and a fuzzy-logic-based system that improves distance estimation accuracy. The lateration BLE-RSSI method is based on an effective and combinatorial BLE anchors selection and the fuzzy-logic based system on a fuzzy classifier which replaces the traditional LDPL models used to estimate distance.

While setting the LDPL model parameters and evaluating the BLE signals (transmitted from various mobile devices), we identified the following aspects. First, the behavior of BLE signal propagation indoors and under LOS does not follow the expected logarithmic attenuation. Instead, it varies depending on the transmitter device and indoor environment. We consider that this behavior is mainly due to the diverse power transmission of each device and signal fluctuations generated by the environment's geometry. So, it is impossible to provide a unique set of LDPL model parameters that work for various devices and scenarios. Nevertheless, an average of the parameter values can give a moderate distance accuracy if the conditions are similar in both devices and the environment. Second, the pre-processed (filtering and smoothing) of BLE signals affects the selection of model parameters ($RSSI(d_0)$ and η) and consequently, the accuracy of the estimated distance. Among the filters tested, the filter based on the moving average provides a lower distance error in most cases.

We found the following findings based on our fuzzy-logic based system's performance analysis and its comparison with the LDPL model approach. First, indoors, our proposed scheme outperforms the LDPL model distance accuracy. This is because the designed triangular membership functions can encompass the data dispersion caused by the environmental characteristics. Also, the defuzzifier module merges the fuzzy set output through the center of gravity algorithm. Second, our proposed system behaves better than the LDPL-based outdoors. Although our scheme presents similar performance indoors and outdoors, the difference is that the LDPL model approach performs better outdoors than indoors. It is due to less BLE signal propagation fluctuating (e.g., no propagation obstructions) and following a logarithmic attenuation pattern. So, the LDPL model can model the signal propagation better outdoors than indoors. However, a limitation of our proposed approach is that it cannot offer robustness against power transmission variation due to how we set the membership functions. We define them based on the first, second, and third quartile values of the signals measured at each reference point. So, if the power transmission of each device is different from the one used in training, the membership functions are shifted and provide erroneous estimations.

Regarding the lateration method based on effective selection and combinatorial BLE anchors selection, the analysis of the results demonstrated that our method, in comparison with the traditional lateration method, reduces the positioning error by between 5% (median) and 16% (90 percentile). Also, the use of an ensemble approach that averages the traditional and our proposed method outperforms both. Although our method does not use sine and cosine computations to select the adequate anchors as in GDOP, one of its limitations is the computational load to evaluate all possible combinations of deployed anchors. Therefore, to guarantee computational feasibility, we limited the maximum total number of available BLE anchors to 9 ($K = 9$ in Eq. 4.6). With respect to fingerprinting–k-NN evaluation, the analysis of the effect of the numbers of BLE anchors used to build the radio map, and the values of k on positioning accuracy demonstrated the following: first, a low number of BLE anchors (below ten BLE anchors) decrements the positioning accuracy considerably in fingerprinting. Second, for positioning accuracy, an increased value of k is less important than the increase of the number of BLE anchors. So, the design of methods that help to improve the positioning accuracy of RSSI-lateration and fingerprinting–k-NN methods when there are few BLE anchors available in the environment is an open issue. In the next chapter, we propose collaborative approaches that enhance the positioning accuracy of RSSI-lateration and fingerprinting–k-NN methods.

5 COLLABORATIVE INDOOR POSITIONING SYSTEMS

Collaborative Indoor Positioning Systems (CIPSs) focused on human positioning, which aim to improve the performance of traditional Indoor Positioning Systems (IPSs) through collaboration among neighboring devices, have been investigated since 2006, and have had a growing interest within the scientific community ever since [3]. During this time, the increasing availability of mobile/wearable devices with diverse built-in technologies has sped up the development of indoor positioning applications based on them [22]. Within the enabling technologies, Bluetooth Low Energy (BLE) and IEEE 802.11 Wireless LAN (Wi-Fi), together with lateration and fingerprinting-based methods, have been widely investigated both as non-collaborative and collaborative indoor positioning solutions [3].

Lateration and fingerprinting-based methods present good performance for positioning devices in simulations and controlled environments. However, in real environmental conditions, their performance dramatically decreases. The results presented in Chapter 4 showed that the position accuracy of these methods depends on the number and distribution of the available anchors. Also, Received Signal Strength Indicator (RSSI)–lateration methods depend on the proper modeling of the signal propagation (e.g., Logarithmic Distance Path Loss (LDPL)). Although we improved the positioning accuracy of the lateration methods by proposing an effective combinatorial anchor selection method and the LDPL through a model based on fuzzy logic, these solutions present limitations to work with heterogeneous devices and diverse scenarios. In addition, it cannot model diverse Non-line-of-sight (NLOS) conditions and provide robustness against conditions not identically to those present in previously trained models reflecting the captured environment.

Therefore, in this chapter, we propose a versatile and straightforward CIPS baseline scheme designed for developing CIPSs capable of improving the performance (i.e., position accuracy) of traditional IPSs, at least in specific environmental situations. In detail, we develop and experimentally evaluate two variants of a mobile device-based CIPS based on Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs) considering different technologies (i.e., Wi-Fi and BLE), methods (i.e., lateration and fingerprinting-based), NLOS conditions, and two real-world scenarios.

The main contributions of this chapter are:

- We propose a mobile device-based CIPS baseline scheme using MLP ANNs to enhance the performance (e.g., position accuracy, computational complexity, etc.) of traditional IPSs, considering specific environmental conditions.
- We propose two variants of a mobile device-based CIPS using MLP ANNs. The first aims to improve the positioning accuracy of traditional IPSs based on BLE–RSSI lateration methods. The second aims to enhance the positioning accuracy of traditional IPSs based on BLE–fingerprinting–k-Nearest Neighbors (k-NN) and Wi-Fi–fingerprinting–k-NN methods.
- We experimentally validate and demonstrate the usefulness of our proposed mobile device-based CIPSs to enhance the positioning accuracy of traditional indoor positioning systems based on RSSI-lateration and fingerprinting–k-NN methods.
- We experimentally analyze and validate the suitability of our proposed mobile device-based CIPSs using MLP ANNs under various conditions (i.e., diverse distribution of collaborative users/devices in the environment, different NLOS conditions) and indoor environments (office and lobby scenarios).
- We present the benefits of our proposed approaches and enlist their limitations.

5.1 Collaborative indoor positioning system baseline scheme

The analysis of the results and recommendations presented in our systematic review on CIPSs (Chapter 2) provided the foundation for structuring our mobile device-based CIPS baseline scheme. Mainly in the breakdown of the primary parts of the system, its architecture, and infrastructure. One of the fundamental features considered is the modular design of the system. A modular design allows us to divide the system into parts that can be evaluated, configured, improved, and re-used independently. Furthermore, the modular design allows us to exchange and test diverse modules among various proposed CIPSs that follow the same modular structure. Unlike the breakdown of the CIPSs introduced in our systematic review (Section 2.3.4), which divided the CIPSs into two phases (non-collaborative and collaborative), we designed our baseline considering three phases - the two previously mentioned and a new one. The additional phase aims to include information about the heterogeneous devices used in CIPSs. Specifically, the additional phase is dedicated to performing the collaborative devices' calibration & registration process. By strictly separating this calibration & registration step into a different phase, we further improve the modularity of the system.

Another important feature of CIPSs corresponds to architecture. We considered a decentralized architecture in our CIPS baseline founded on the advantages of decentralized systems over centralized ones, identified in our systematic review. Under the decentralized architecture, each device can execute the algorithms and exchange information with the neighboring devices without using a central unit or server. In addition, the decentralized architecture enables each of the devices, in the non-collaborative phase, to execute positioning algorithms or use technologies and techniques different from the rest of the devices. For example, some devices can use BLE, ranging, and lateration, while the rest uses Wi-Fi, fingerprinting, and k-NN.

The infrastructure needed for our CIPS baseline scheme depends on the technology implemented in the non-collaborative phase. The non-collaborative phase can be used as infrastructure-based (e.g., using BLE anchors deployed in the environment for positioning purposes) or infrastructure-less (e.g., using Wi-Fi Access Points (APs) present in the environment as a signal of opportunity). In contrast, the proposed collaborative phase is infrastructure-less, as it uses embedded wireless technologies in the mobile devices. Overall, the CIPS baseline is considered infrastructure-less when both phases are fully infrastructure-less, and hybrid when the non-collaborative phase is infrastructure-based.

The principal aims of our proposed CIPS baseline are:

- To provide a mobile device-based CIPS baseline using MLP ANNs to enhance the performance (e.g., position accuracy, computational complexity, etc.) of traditional IPSs.
- To propose a versatile and straightforward CIPS baseline scheme that allows us to develop CIPSs and evaluate the performance of diverse collaborative indoor positioning technologies, techniques, and methods.

Figure 5.1 presents the scheme of our proposed CIPS based on MLP ANNs to improve the accuracy of the traditional IPSs. The baseline is divided into three phases as follows.

- Calibration phase: the first phase is dedicated to calibrating and registering the devices used in the collaborative approach.
- Non-collaborative phase: the second phase, the non-collaborative phase, is devoted to the stand-alone IPS algorithm used to estimate the position of each device/user.
- Collaborative phase: the third phase, the collaborative phase, is dedicated to collaboratively improving the estimated position of the target device/user. In our proposed scheme, this phase is subdivided into four main parts as follows.
  - A. Information exchange between devices.
  - B. Estimation of the relative distance between devices.
  - C. Collaborative algorithm to estimate the position of the target device/user collaboratively.
  - D. Algortitm to combine the positions estimated in the stand-alone phase (first phase) with the collaborative estimated position (third phase - part C).

In Section 5.2 and Section 5.3, we demonstrate the usefulness of the proposed CIPS baseline scheme to develop CIPSs that enhance the positioning accuracy of traditional IPSs. To this end, in Section 5.2, we present and evaluate the first variant of mobile device-based CIPS using MLP ANNs and BLE technology to improve the positioning accuracy of traditional IPSs based on BLE–RSSI lateration methods. Similarly, in Section 5.3, we present and evaluate the second variant of mobile device-based CIPS using MLP ANNs to enhance the positioning accuracy of traditional IPSs based on BLE–fingerprinting–k-NN and Wi-Fi–fingerprinting–k-NN methods. The corresponding sections present additional details about the developed CIPSs, their phases, and their setting.

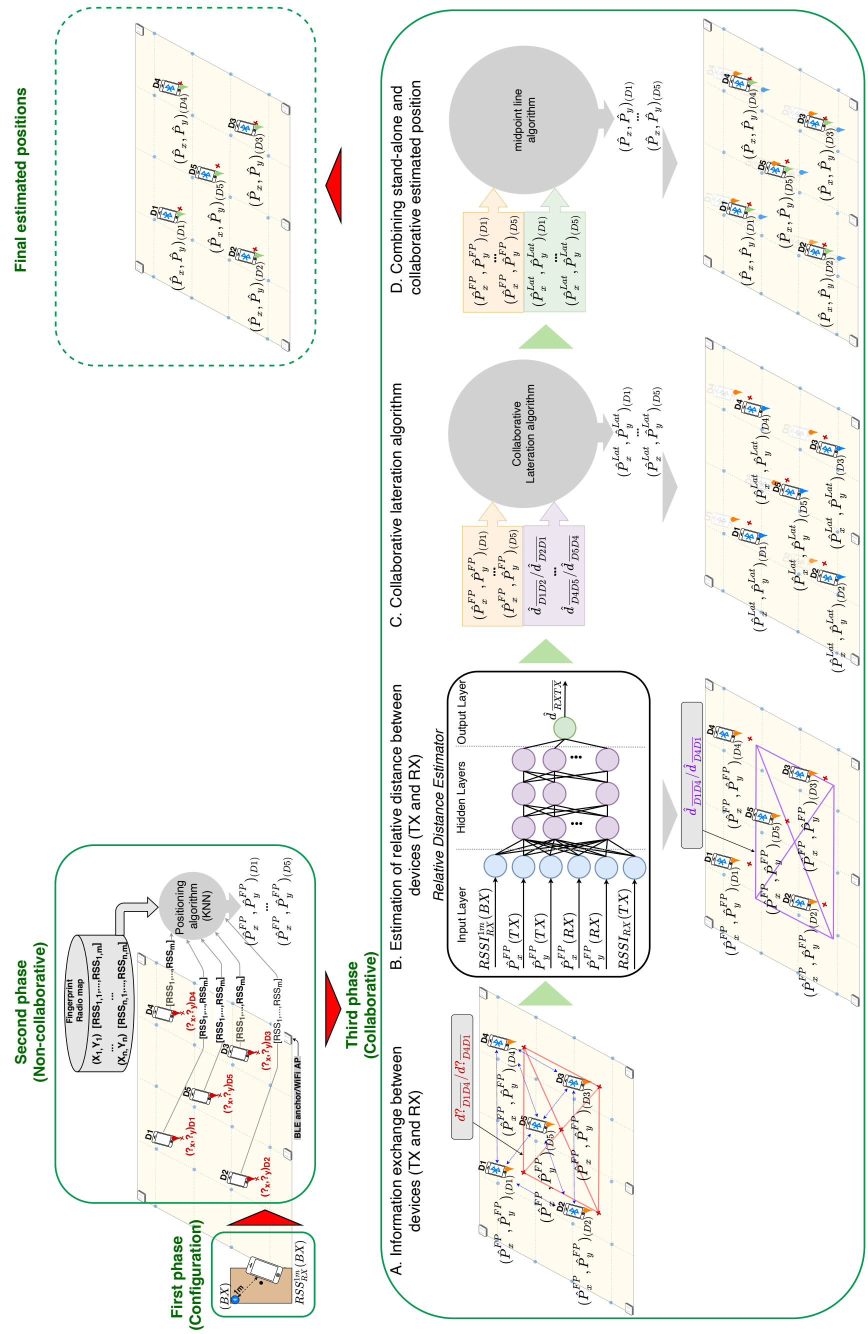


Figure 5.1 Scheme of the proposed CIPS baseline.

5.2 Collaborative approach for BLE–RSSI lateration

IPSs based on BLE–RSSI lateration methods under ideal environments (e.g., testbeds with an appropriate amount and distribution of BLE anchors and in Line-of-sight (LOS) conditions) and simulations present high positioning accuracy and a position error in the range of $0.8\,\mathrm{m}$ to $1.3\,\mathrm{m}$ [197, 201]. Contrary, in real-world environments (e.g., malls, classrooms, offices, bookstores), which include ample NLOS conditions and anchor deployments that are not always optimized for positioning activities, the positioning accuracy decreases drastically. Moreover, they depend on the modeling of the Radio Frequency (RF) signal propagation in each environment to convert RSSI values into distances, which is not trivial. For that reason, although the use of BLE-RSSI anchors is feasible for proximity detection applications [202, 203] and easy to implement, its use for more accurate positioning applications is still an open issue.

In this section, we propose a mobile device-based CIPS using MLP ANNs to improve the positioning accuracy of traditional IPSs based on BLE–RSSI lateration methods. Our approach copes with three principal drawbacks of lateration methods that decrements their positioning accuracy. First, reducing the inaccuracy caused by NLOS conditions and deficient anchors deployment. Second, minimizing the influence caused by inefficient modeling of the signal propagation. Third, mitigating the effect of device heterogeneity on positioning accuracy. Our approach's application covers scenarios with limited BLE anchors deployment but with a moderate number of mobile devices/users, and the latency of users' position is moderate. Some application examples include tracking patients in hospitals, staff in government offices, and people in shopping malls.

Our proposed collaborative approach uses the surrounding mobile devices (collaborative devices) to extend the positioning network. The collaboration between them starts with the information sharing (e.g., its current position estimated by the stand-alone lateration approach and the BLE–RSSI values measured) and processing by a MLP ANNs model to estimate the relative distance between them. Then, that information is used to estimate the device's collaborative position using lateration. Finally, using a midpoint algorithm, we merge the estimated position of both collaborative and non-collaborative parts to provide a final estimated position of each collaborative device. Our approach uses a neural network model to replace the

LDPL model. LDPL models mainly estimate the distance based on theoretical signal attenuation formulas. With the neural network model, the distance estimation is improved by considering the relation between distance and RSSI patterns, pairwise device position, identification of devices (transmitter and receiver), and variation of RSSI measurements due to the devices' hardware heterogeneity. In the next subsections, our proposed collaborative approach is detailed. Furthermore, the proposed collaborative and traditional lateration approaches are compared and evaluated in a real-world scenario, and their main results are presented and discussed.

The main contributions are:

- We propose a variant of mobile device-based CIPS using MLP ANNs to improve the positioning accuracy of traditional IPSs based on BLE–RSSI lateration methods.
- We demonstrate through the development and evaluation of our CIPS the usefulness of the CIPS baseline scheme proposed in Section 5.1. We detail the use and setting of each of its phases and components.
- We present a novel model to estimate the relative distance between collaborative mobile devices based on an MLP ANNs approach. Our proposed model provides a better modeling of signal propagation in LOS and NLOS conditions with respect to the models based on LDPL, as well as, the receiver devices variables involved in the estimation of the distance.
- We experimentally evaluate and demonstrate that our CIPS outperforms a traditional lateration approach under a real indoor scenario (office scenario) with poor density and distribution of BLE anchors and diverse NLOS conditions.

5.2.1 First phase: calibration phase

The first phase of the collaborative approach is the calibration and registration of mobile devices, which identifies mobile devices and stores the required parameters to be processed in the collaborative algorithm for each device. In this work, the RSSI values to $1\,\mathrm{m}$ are gathered per device. The procedure is requesting each new user to stand at a floor mark, $1\,\mathrm{m}$ away from a reference anchor (BX) during $60\,\mathrm{s}$, in order to measure and record the RSSI values (i.e., $RSSI_{RX}^{1m}(BX)$), then averaged them to get only one value per device. Experimentally it was determined that $60\,\mathrm{s}$ is enough time to compensate for any delay in the transmission of the BLE signal and remove any anomaly detected. The reference anchor broadcasts BLE advertisements and can be installed, for example, at the main entrance of the scenario. For each (new) device, this quick calibration process is only carried out once. A practical implementation of this procedure could be to connect the calibration with the electronic door-locking system applications installed in mobile devices and reduce measurement time (e.g., 5 s).

5.2.2 Second phase: non-collaborative phase

The second phase corresponds to the non-collaborative phase. In our specific case, we implement a stand-alone BLE-RSSI lateration method, which aims to estimate the initial position of each device/user using the Ground-Truth (GT) coordinates of the BLE anchors distributed in the scenario and the RSSI values measured. The lateration method used to estimate the position relies on the LDPL model, a minimization problem, and the Levenberg-Marquardt algorithm for weighted nonlinear least-squares to solve the minimization problem. A detailed description of the lateration method is provided in Section 4.2.1.1. Also, its mathematical formulation is provided in Eq. (4.4) and Eq. (4.5).

The correlation between the attenuation of RSSI as it propagates through space and the distance, between the transmitter and the receiver, is described by the LDPL model and mathematically expressed by the equation (5.1) [191]:

$$RSSI_{RX}^{d}(TX) = RSSI_{RX}^{1m}(BX) - 10\,\eta\,log\left(\frac{d}{d_0}\right) \tag{5.1}$$

where $RSSI_{RX}^{d}(TX)$ denotes the RSSI value measured by the receiver (RX), which is at a distance d from the mobile device transmitter (TX); $RSSI_{RX}^{1m}(BX)$ denotes the RSSI value measured by the receiver (RX), which is at a distance of 1 m from the BLE anchor transmitter (BX); The transmitter could be a BLE anchor or a mobile device; and η is the path-loss attenuation factor.

The stand-alone lateration approach is described by the Algorithm 2, and its working procedure is outlined as follows:

- **1st step:** Gather the RSSI from BLE anchors ($RSSI_{RX}^{d}(TX)$) that are reachable in a time window (tw) of 60 s, excluding those that are not part of the deployment scenario (input data for Algorithm 2);

- **2nd step:** Group the RSSI gathered in **1st step** by anchors, then remove the outliers of each group, which are those values outside of 25 and 75 percentiles (lines 1–2 in Algorithm 2);
- **3rd step:** Average RSSI value per anchor by applying the average operator to the RSSI values in each group. (line 3 in Algorithm 2);
- **4rd step:** Choose those BLE anchors whose averaged RSSI value is equal to or within a pre-set threshold (lines 4–8 in Algorithm 2);
- **5th step:** Estimate the relative distance between the chosen BLE anchors in **4rd step** and the target position of the device/user by applying the LDPL model (eq.(5.1)) and considering the RSSI values and η (line 9 in Algorithm 2);
- **6th step:** Estimate the position of the device/user ($\hat{\mathbf{P}}^{Lat1}$) by applying the Levenberg-Marquardt Weighted Least Squares (L-MWLS) lateration method, which uses the data computed in the **5th step**, the weights, and the GT of the BLE anchors. In the weighted centroid calculation, the weight for every BLE anchor is calculated as the inverse of the estimated distance between the anchor and the device/user. $Lat1$ refers to the L-MWLS lateration method in the stand-alone phase, and
- **7th step:** Share the estimated position, $\hat{\mathbf{P}}^{Lat1}(RX) = [\hat{P}_x^{Lat1}(RX), \hat{P}_y^{Lat1}(RX)]$.

The $threshold$ and the path-loss attenuation factor (η) values are $-83\,\mathrm{dBm}$ and 2.1 respectively, as we used before in [6] and which are aligned with values proposed in the literature [197]. The devices used in the collaborative positioning approach have their own $RSSI_{RX}^{1m}(BX)$ value according to the data gathered during the device calibration phase (see Table 5.1).

5.2.3 Third phase: collaborative phase

The third phase corresponds to the collaborative phase, which uses information from the neighboring mobile devices, including the position of the receiver and transmitter devices estimated in the stand-alone phase, the measured BLE-RSSIs, and the RSSI at $1\,\mathrm{m}$ of the receiver to estimate the position of the device/user collaboratively. Then, we calculate the final position of the device/user combining the collaborative and independent estimates to improve the latter. In the collaborative phase, the collaborative devices/users extend the original coverage area of the network by acting as an

Algorithm 2 Stand-alone lateration

Input: Deployed anchors information collected within a time window tw: $RSSI^{d}_{RX}(TX)$ values and GT
Input: LDPL: $\eta = 2.1$ and $RSSI^{1m}_{RX}(BX)$
Input: $threshold$
Output: Estimated device/user position $\hat{\mathbf{P}}^{Lat1}(RX)$

Group the $RSSI^{d}_{RX}(TX)$ values by beacon
Remove $RSSI^{d}_{RX}(TX)$ outliers values of each group
Average $RSSI^{d}_{RX}(TX)$ values of each group : $\overline{RSSI^{d}_{RX}(TX)}$
for $i \leftarrow 1$ **to number of** $\overline{RSSI^{d}_{RX}(TX)}(i)$ **do**
    if $(\overline{RSSI^{d}_{RX}(TX)}(i) \geq threshold)$ **then**
        Include i-th anchors to reference anchors set $(ref_{anchorset})$
    end if
end for
Estimate the distances between anchors of $ref_{anchorset}$ and the device/user position using Eq.5.1, η and $RSS^{1m}_{RX}(BX)$
Estimate the device/user position ($\hat{\mathbf{P}}^{Lat1}(RX)$) using the Levenberg-Marquardt Weighted Least Squares method
Share the estimated device/user position ($\hat{\mathbf{P}}^{Lat1}(RX) = [\hat{P}^{Lat1}_{x}(RX), \hat{P}^{Lat1}_{y}(RX)]$)

extra anchor of the network (extended ad-hoc position network based on collaborative devices).

The collaborative phase is comprised of four major components: A) exchange of information between devices; B) a MLP neural network to estimate the relative distance between the devices; C) a collaborative lateration algorithm, which collaboratively estimates the position of the target device/user; and D) a method to combine the stand-alone and collaborative position estimations.

5.2.3.1 A. Information exchanged between devices/users

Nowadays, broadcasting BLE advertisements is possible thanks to updated mobile and wearable device operating systems, which now allow them to act as BLE anchors and share information between them [167]. As a consequence, they enable the development of collaborative systems that depend on this feature used in our collaborative positioning system includes: the RSSI received at the receiver from the transmitter ($RSSI_{RX}(TX)$), the RSSI at 1 m ($RSSI^{1m}_{RX}(BX)$) of the receiver obtained after registering the device, and the position of each collaborative device/user estimated by the stand-alone lateration ($\hat{P}^{Lat_1}_{x}(TX)$, $\hat{P}^{Lat_1}_{y}(TX)$, $\hat{P}^{Lat_1}_{x}(RX)$, $\hat{P}^{Lat_1}_{y}(RX)$).

The aforementioned feature data are used as input for the neural network described in the next section and the collaborative algorithm described in Algorithm 3. It should be noted that the sharing data in our proposed CIPS is unidirectional (e.g., surrounding devices sharing information with the receiver).

5.2.3.2 B. Estimation of the relative distance between devices

Figure 5.2 depicts the architecture of the MLP neural network model used to estimate the relative distances between mobile devices. The architecture is composed of one input layer with six neurons, one hidden layer with three neurons, and one output layer. The activation and training functions used are the hyperbolic tangent, and the scaled conjugate gradient backpropagation, respectively, and 50 epochs were used. Additional details on the selection of the MLP neural network's hyperparameters are presented in Section 5.2.4.

The input of the MLP neural network model corresponds to the information exchanged between each pair (target device–neighbor device) and the output to the estimated distance of that specified pair. In detail, the six features used in the input are: 1) the $RSSI_{RX}(TX)$, which is the RSSI value of the BLE advertisement transmitted by the transmitter TX and measured by the receiver RX; 2–3) the estimated position coordinates x ($\hat{P}_x^{Lat_1}(TX)$) and y ($\hat{P}_y^{Lat_1}(TX)$) of the transmitter (neighbor device/user), which were estimated by the stand-alone lateration algorithm; 4–5) the estimated position coordinates x($\hat{P}_x^{Lat_1}(RX)$) and y ($\hat{P}_y^{Lat_1}(RX)$) of the receiver (target device/user), which were estimated by the stand-alone lateration algorithm too; and 6) the $RSSI_{RX}^{1m}(BX)$ corresponding to the RSSI value measured at $1\,\mathrm{m}$ of the distance between transmitter and receiver assigned at each mobile device by phase one (see Table 5.1).

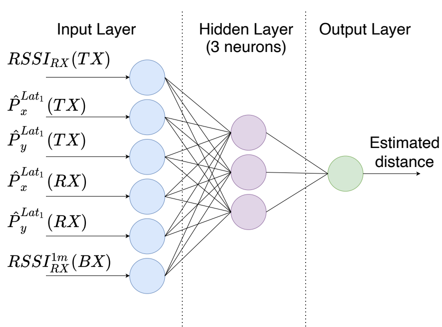


Figure 5.2 MLP neural network model architecture (lateration). Used to estimate the relative pairwise distance between the target and neighboring devices/users.

5.2.3.3 C. Collaborative lateration algorithm

The collaborative lateration algorithm is similar to the algorithm used in the stand-alone phase (see Section 5.2.2). The two principal differences correspond to the data provided to execute the lateration. First, the anchors used by the collaborative lateration algorithm are the neighboring devices/users acting as anchors, whose position is estimated by the stand-alone lateration, instead of the BLE beacons deployed in the scenario with a well-known position. Second, rather than using the LDPL model to estimate the relative distance between neighboring devices/users and the target device/user, we use a MLP neural network model.

5.2.3.4 D. Combining stand-alone and collaborative estimated positions

After the target device's position has been collaboratively estimated using neighboring devices/users as anchors, it is combined with the stand-alone estimation to obtain the final estimated position. To this end, we used a midpoint line algorithm, which is described in Eq. (5.2) and Eq. (5.3).

$$\hat{\hat{P}}_x(RX) = \frac{\hat{P}_x^{lat_1}(RX) + \hat{P}_x^{lat_2}(RX)}{2} \tag{5.2}$$

$$\hat{\hat{P}}_y(RX) = \frac{\hat{P}_y^{lat_1}(RX) + \hat{P}_y^{lat_2}(RX)}{2} \tag{5.3}$$

where $\hat{\hat{\mathbf{P}}}(RX) = [\hat{\hat{P}}_x(RX), \hat{\hat{P}}_y(RX)]$ denotes the final estimated position, with x and y coordinates, of device/user RX, with $RX = \{1, 2....N\}$ and N the number of devices. $\hat{P}_x^{lat_2}(RX)$ and $\hat{P}_y^{lat_2}(RX)$ denotes the position estimated, x and y coordinates, with the collaborative lateration and $\hat{P}_x^{lat_1}(RX)$ and $\hat{P}_y^{lat_1}(RX)$ denotes the position estimated, x and y coordinates, with the stand-alone lateration, both for device/user RX.

5.2.3.5 Full collaborative workflow

The pseudo-code for the collaborative positioning algorithm is described by the algorithm 3. Its inputs correspond to the shared information exchanged by each collaborative device/user within a time window (wt) of $60\,\mathrm{s}$. In detail, the inputs are the RSSI values transmitted by each collaborative device/user ($RSSI_{RX}(TX)$); the estimated position of each collaborative device/user estimated by the stand-alone lateration ($\hat{P}_x^{Lat_1}(TX)$, $\hat{P}_y^{Lat_1}(TX)$, $\hat{P}_x^{Lat_1}(RX)$, $\hat{P}_y^{Lat_1}(RX)$); and the RSSI at $1\,\mathrm{m}$ ($RSSI_{RX}^{1m}(BX)$). The algorithm working procedure is outlined as follows:

- **1nd step:** Group the RSSI readings by device, then remove the outliers from each group based on the interquartile method, which removes those values outside of the range between the 25 and 75 percentile values (lines 1–2 in Algorithm 3);
- **2rd step:** Average the RSSI values per each device/user, getting one average RSSI value per device/user (line 3 in Algorithm 3);
- **3th step:** Estimate the relative distances between the neighboring devices/users and the target device/user, by applying the MLP model (see Figure 5.2). The features used in the input of the ANNs model are: $RSSI_{RX}(TX)$, ($\hat{P}_x^{Lat_1}(TX)$, $\hat{P}_y^{Lat_1}(TX)$), ($\hat{P}_x^{Lat_1}(RX)$, $\hat{P}_y^{Lat_1}(RX)$), and $RSSI_{RX}^{1m}(BX)$ (input values in Algorithm 3);
- **4th step:** Estimate the position of the device/user ($\hat{\mathbf{P}}^{Lat2}(RX)$) by applying the Levenberg-Marquardt Weighted Least Squares (L-MWLS) lateration method, whose input data are the relative distances estimated by the MLP neural network model (**3th step**), the weights, and the estimated positions ($\hat{\mathbf{P}}^{Lat1}$) of the neighboring devices/users. Similarly to the stand-alone algorithm, the weight value for every BLE anchor is calculated as the inverse of its squared distance with respect to the device/user, and
- **5th step:** Compute the final estimated position of the device/user ($\hat{\hat{\mathbf{P}}}(RX)$) using the formula expressed in Eq. (5.2) and Eq. (5.3), considering the estimated stand-alone position ($\hat{\mathbf{P}}^{lat_1}(RX)$) and collaborative estimated position ($\hat{\mathbf{P}}^{lat_2}(RX)$. (RX)) is the identifier of the device/user to estimate its position.

5.2.4 Experiments and results

5.2.4.1 Experimental setup

This section describes the setup of the experiments performed. The experiments aim to evaluate the feasibility and advantages of our proposed collaborative approach in

Algorithm 3 Collaborative module

Input: Collaborative devices information collected within a time window tw: $RSSI_{RX}(TX)$, $\hat{P}_x^{Lat_1}(TX)$,$\hat{P}_y^{Lat_1}(TX)$,$\hat{P}_x^{Lat_1}(RX)$,$\hat{P}_y^{Lat_1}(RX)$, and $RSSI_{RX}^{1m}(BX)$

Output: Improved estimated device/user position ($\hat{\hat{\mathbf{P}}}_{dev}(n)$)

1: Group the $RSSI_{RX}(TX)$ values by device
2: Remove $RSSI_{RX}(TX)$ outliers values of each group
3: Average $RSSI_{RX}(TX)$ values of each group: $\overline{RSSI_{dev}}(i)$
4: Estimate the relative distance between the target device and the near collaborative devices using the trained ANN model
5: Estimate the device/user's position ($\hat{\mathbf{P}}^{Lat_2}(RX)$) using the Levenberg-Marquardt Weighted Least Squares (L-MWLS) lateration method
6: Compute the final estimated device/user's position ($\hat{\hat{\mathbf{P}}}(RX)$) using the midpoint line algorithm in Eq. (5.2) and Eq. (5.3)

comparison with a traditional BLE–RSSI lateration baseline to counteract insufficient BLE anchor deployment and NLOS conditions in the scenario. In particular, we assess and compare both approaches' positioning accuracy in a realistic scenario.

The scenario used to carry out the experiments corresponds to a real office located at Universitat Jaume I, Spain, which covers an approximate area of $10.76\,\mathrm{m}$ by $16.71\,\mathrm{m}$. The 3D representation, which illustrated the complexity of the environment, is shown in Figure 3.3(**b**). The scenario is characterized by NLOS conditions, principally due to the scenario's furniture (i.e., pillars, desks, chairs, and bookshelves). In the scenario, six diverse collaborative configurations (configurations 1 – 6) were used, considering five mobile devices (devices 1, 2, 3, 4, and 6) to create diverse NLOS cases among devices. The configurations are illustrated in Figure 5.3. A detailed description of them is provided in Section 3.2.4 (Subset-C). Also, we deployed seven BLE anchors, whose transmission power and period are $-4\,\mathrm{dBm}$ and $250\,\mathrm{ms}$, respectively. Complementary information of the office scenario is available in Section 3.2.2.

A thorough data collection was carried out in this office scenario. First, during the calibration and registration process, the five collaborating mobile devices were registered (see Section 5.2.1) and each mobile device measured its $RSSI_{RX}^{1m}$ using a fixed BLE anchor from the scenario. The $RSSI_{RX}^{1m}$ values corresponding to each of the five mobiles used in the experiment, as well as the mobile devices used (devices 1, 2, 3, 4, and 6), are summarized in Table 5.1. It should be noted that each $RSSI_{RX}^{1m}$ value depends on the mobile device model and is utilized as a means of identification in the MLP ANN model. The $RSSI_{RX}^{1m}$ values are within the range $-78.79\,\mathrm{dBm}$ to $-62.39\,\mathrm{dBm}$.

Table 5.1 $RSSI^{1m}_{RX}(BX)$ values by device (office scenario).

ID/RX	Device name	Model	$RSSI^{1m}_{RX}(BX)$ values (dBm)	Scenario
1	Galaxy S8	SM-G950F	-68.88	Office
2	Lenovo Yoga Book	Lenovo YB1-X90F	-74.75	Office
3	Galaxy A7 Duos	SM-A7100	-62.39	Office
4	Galaxy S6	SM-G920F	-62.99	Office
6	Galaxy A5	SM-A500FU	-78.79	Office

Next, the collaborative configurations 1 to 6 (described in Section 3.2.4 (Subset-C)) were considered. Specifically, for 2 hours, the five devices, in each configuration, broadcasted and recorded data from neighboring devices, including the BLE anchors. According to the low latency mode supported by Android devices [204], the mobile devices' broadcast latency was set to $100\,\mathrm{ms}$. Since the mobile devices are not ad-hoc positioning devices, the broadcast latency presents variations. The main causes are the power-saving modes installed in the device's operative system and the tasks execution priorities. Each configuration's data was gathered separately and at a different time. As previously stated, the path-loss factor for the lateration approach based on the LDPL is $\eta = 2.1$ for all five devices.

The distribution of the mobile devices (i.e., devices 1, 2, 3, 4, and 6) in each configuration together with the BLE anchors (i.e., anchors 1, 4, 6, 9, 10, 17 and 19) considered in the office scenario is shown in Figure 5.3. Table 5.2 and Table 5.3 summarize the GT coordinates of mobile devices and BLE anchors, respectively.

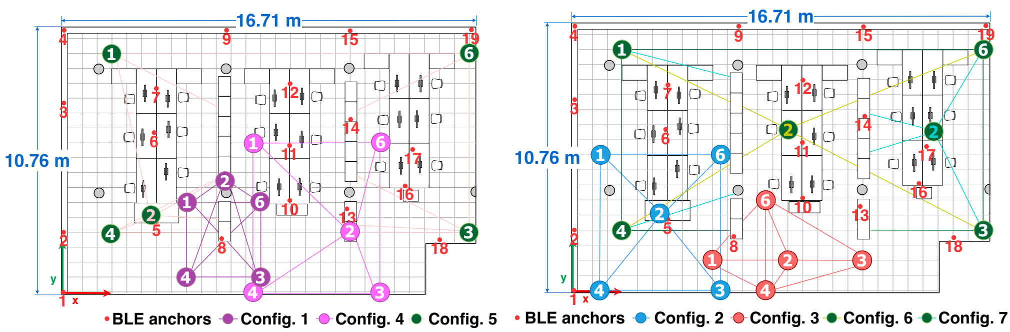
Table 5.2 Devices' Ground truth in each configuration in the office scenario.

ID/RX	Ground truth (m)														Scenario
	Config. 1		Config. 2		Config. 3		Config. 4		Config. 5		Config. 6		Config. 7		
	x	y	x	y	x	y	x	y	x	y	x	y	x	y	
1	5.05	3.7	1.33	6.1	6.93	1.3	7.75	6.1	2.05	9.7	2.05	9.7	2.05	9.7	Office
2	6.55	4.55	4.49	3.05	9.93	1.3	11.75	2.75	3.6	3.3	8.7	6.4	14.66	6.45	Office
3	8.05	0.7	7.66	0.1	12.93	1.3	12.75	0.1	16.45	2.5	16.45	2.5	16.45	2.5	Office
4	5.05	0.7	1.33	0.1	9.03	0.1	7.75	0.1	2.05	2.5	2.05	2.5	2.05	2.5	Office
6	8.05	3.7	7.66	6.1	9.03	3.7	12.75	6.1	16.45	9.7	16.45	9.7	16.4	9.7	Office

We divided the data acquired, in the six configurations, into two datasets, ensuring that both datasets cover different zones of the scenario and the distances between devices and between anchors vary. Each dataset contributes to diverse objectives: configurations 1, 4, and 5 (see Figure 5.3(**a**)) are used for testing the model, and configurations 2, 3, and 6 (see Figure 5.3(**b**)) are used for evaluation. The second

Table 5.3 Ground Truth of BLE anchors deployed in the office scenario.

BLE anchor (No.)	x (m)	y (m)	TX Power (dB)	TX Period (ms)
1	0	0	-4	250
2	0	2.61	-4	250
3	0	7.66	-4	250
4	0	10.68	-4	250
5	3.88	3.54	-4	250
6	3.78	6.51	-4	250
7	3.87	8.64	-4	250
8	6.45	2.13	-4	250
9	6.68	10.64	-4	250
10	9.2	3.7	-4	250
11	9.08	5.95	-4	250
12	9.18	8.71	-4	250
13	11.4	3.6	-4	250
14	11.54	7.18	-4	250
15	11.54	10.65	-4	250
16	13.95	4.34	-4	250
17	14.2	6.05	-4	250
18	15.65	1.71	-4	250
19	16.65	10.65	-4	250



(a) Configurations 1, 4, and 5 used in the testing

(b) Configurations 2, 3, 6 and 7 used in the training & evaluation

Figure 5.3 Distribution of the configurations used in the training & evaluation and testing in the office scenario.

dataset (training) was randomly divided into training (70%) and validation (30%) with 741143 and 185285 samples, respectively, to tune the MLP neural network. The testing dataset contains 936103 samples and it was used to test the MLP ANNs for relative distances, and implement the BLE-RSSI lateration baseline and collaborative approach.

The office scenario used presents different adverse conditions from the point of view of positioning. The most important are: diverse and strong NLOS generated by the obstacles in the scenario; an area with low Geometric Dilution of Precision

(GDOP), poor number and distributions of anchors for positioning (only 7 BLE anchors); and device heterogeneity (5 diverse mobile devices) for the collaborative phase. Our proposed collaborative model aims to increase the coverage area of the BLE anchors deployed in the scenario through the use of collaborative devices, and replace the LDPL model with a MLP ANNs, which estimate the relative distance considering the receiver and emitter position, its RSSI values and the calibration of RSSI (at $1\,\mathrm{m}$) to mitigate the mobile device heterogeneity effect.

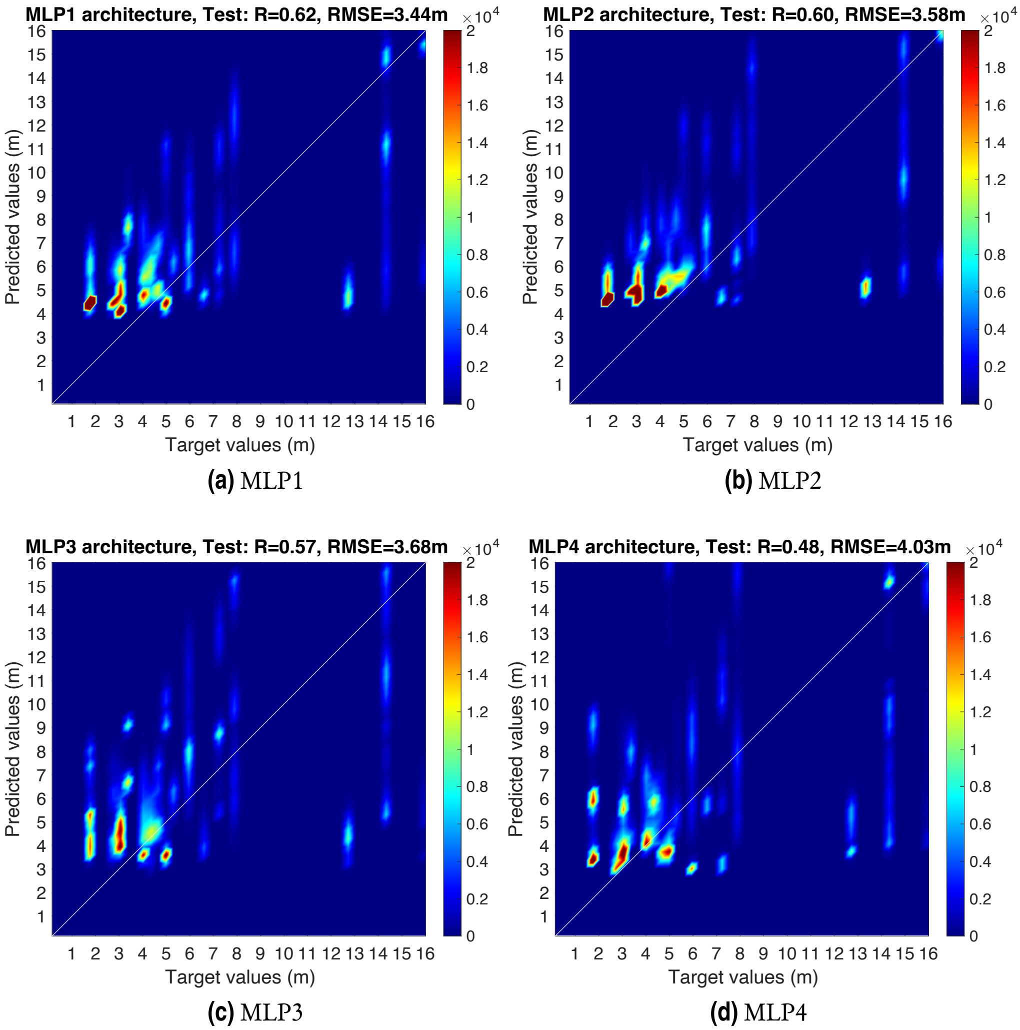
5.2.4.2 Tuning the Multilayer Perceptron (MLP) neural network

In order to define the most suitable MLP architecture and its hyperparameters for our model, we evaluate four architectures. The hyperparameters considered were the number of hidden layers (1 and 2), the number of hidden neurons and the activation function used among the log-sigmoid (logsig) and hyperbolic tangent sigmoid (tansig). It is well-known that in the tunning of MLP neural networks there is no standard method to set the number of hidden layers and the number of neurons by layer. Nevertheless, some initial considerations could be useful in the tuning. So, in our case, we first consider 2 architectures with 1 hidden layer as a starting point, since it can model a wide number of nonlinear problems, and is useful for defining the activation function. Then, we consider 2 architectures with an extra layer to try to improve the results. Regarding the maximum number of neurons tested in each layer, we use as a reference two times the number of neurons in the input layer. The hyperparameters set up for each architecture are detailed in Table 5.4.

Table 5.4 Tested MLP architectures and hyperparameters for office scenario. Source [21].

Parameters	MLP1	MLP2	MLP3	MLP4
No. Input layers	1	1	1	1
No. Hidden layers (HLs)	1	1	2	2
No. Output Layer	1	1	1	1
No. Neurons HL1	3	3	6	12
No. Neurons HL2	-	-	3	6
Training function	trainscg			
Activation function	tansig	logsic	tansig	tansig
Performance function	Mean Square error			

Before discussing the main results of both, the lateration baseline and our proposed collaborative approach, we introduce the results obtained from the evaluation of the four proposed MLP architectures with the training dataset to determine which of them provides the most accurate estimation of relative distances. The results of comparing the real distance with the estimated distance in each of the 4 neural network architectures MLP are presented in Figure 5.4 through density scatter plots, as well as their correlation coefficient (R) and the Root Mean Square Error (RMSE).



(a) MLP1 **(b)** MLP2 **(c)** MLP3 **(d)** MLP4

Figure 5.4 Target vs Predicted distances from the test dataset estimated with MLP1–MLP4 architectures (Office escenario–BLE-lateration).

Based on the information presented in Figure 5.4, we can observe that one hidden layer MLP architectures (MLP1 and MLP2) have lower RMSE than the two hidden layer ones (MLP3 and MLP4), and a greater correlation coefficient, namely 0.62 and 0.60 for MLP1 and MLP2, respectively. Consequently, in terms of accuracy, one hidden layer MLP architectures are better able to estimate the distance. In particular, comparing MLP1 and MLP2 through the density scatter plots illustrated in Figure 5.4(**a**) and (**b**), respectively, we notice that the former (MLP1), which uses a hyperbolic tangent sigmoid activation function (tansig), has a higher density of predicted values near to the real values than MLP2, which uses a log-sigmoid activation function. Moreover, we can observe that within the range $3\,\mathrm{m}$ to $6\,\mathrm{m}$ and near to $15\,\mathrm{m}$ the density increase. The findings of high-density values near the short distance show that the MLP architecture has the ability to enhance the estimated positioning accuracy in CIPS scenarios with a high density of collaborative mobile devices (i.e., when the distance between neighboring devices is short).

After evaluating the 4 different MLP architectures, the MLP1 with a single hidden layer (3 neurons), a hyperbolic tangent sigmoid activation function, and a scaled conjugate gradient backpropagation training function was chosen to estimate the relative distance using BLE–RSSI data.

5.2.4.3 Results of the collaborative model

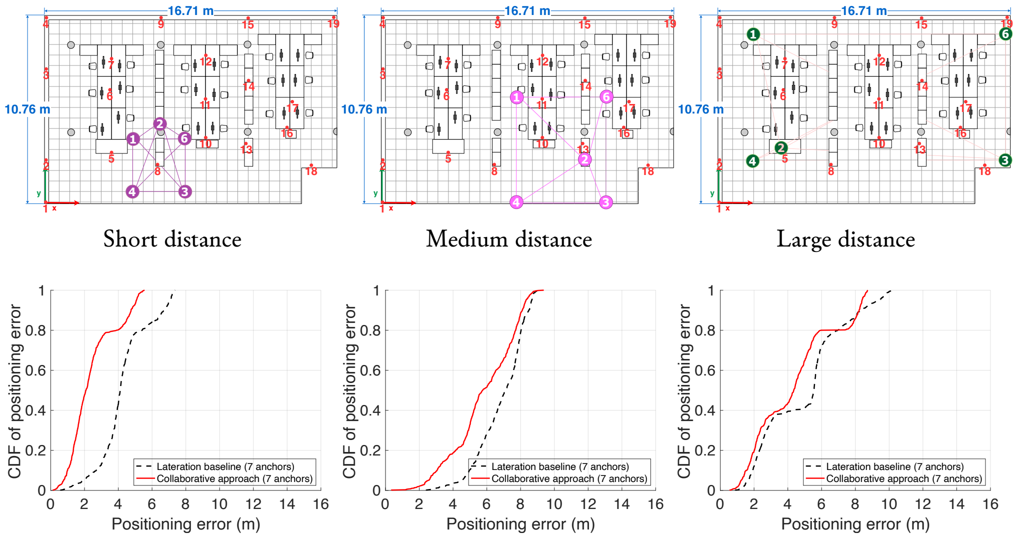
The principal results of the evaluation of our CIPS using MLP ANNs (collaborative approach) and the stand-alone lateration (lateration baseline) considering the evaluation metrics RMSE, mean, median, 75^{th}, and 90^{th} percentile and the relative difference between them. Specifically, we present the results of each configuration used for testing (configurations 1, 4, and 5) independently. Table 5.5 summarizes the results of our collaborative approach and the lateration baseline considering the aforementioned metrics. The down arrows in the table indicate that our proposed CIPS decreases the error with respect to the baseline in the percentage indicated.

Figure 5.5 shows the Empirical Cumulative Distribution Function (ECDF) plots of each configuration and above them the sketch of the corresponding configuration. The red lines represent the result for CIPS using MLP ANNs (collaborative approach) and the black dashed lines for the stand-alone lateration (lateration baseline). In detail, Figure 5.5(**a**) presents the ECDF of configuration 1, Figure 5.5(**b**), and Figure 5.5(**c**) presents the ECDF of configuration 5, whose results are used to evaluate the effect of short, medium and large distance between collaborative devices

Table 5.5 Main results metrics provided by the lateration baseline and our proposed collaborative approach.

	Lateration baseline			Collaborative approach					
	Error (m)			Error (m)			Diff		
Eval. metric	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5
RMSE	4.52	6.98	5.5	2.77	6.1	4.94	↓ 38.72%	↓ 12.61%	↓ 10.18%
Mean	4.29	6.85	4.94	2.42	5.8	4.34	↓ 43.59%	↓ 15.33%	↓ 12.15%
Median	4.11	7.12	5.54	2.09	5.75	4.35	↓ 49.15%	↓ 19.24%	↓ 21.48%
75^{th} percentile	4.76	7.92	6.2	2.93	7.49	5.49	↓ 38.45%	↓ 5.43%	↓ 11.45%
90^{th} percentile	6.72	8.48	8.38	4.75	8.1	8.22	↓ 29.32%	↓ 4.48%	↓ 1.91%

on positioning accuracy, respectively.



(a) Configuration 1 **(b)** Configuration 4 **(c)** Configuration 5

Figure 5.5 CDF of the lateration baseline and collaborative approach (7 BLE anchors) of configurations 1, 4, and 5 in the office scenario.

5.2.5 Discussion

In this section, we presented a variant of mobile device-based CIPS using MLP ANNs to improve the positioning accuracy of traditional IPSs based on BLE–RSSI lateration methods used under challenging environmental conditions, such as hardware heterogeneity, strong NLOS and unstable signal strength conditions, and unfavorable distribution of few BLE anchors (i.e., anchors 1, 4, 6, 9, 10, 17 and 19 in

Figure 5.3). Our approach is divided into three phases. The first phase is dedicated to calibrating and registering the new devices, used in the collaborative approach, through the registration of them and a set of RSSI baseline measurements at 1 m. The second phase corresponds to the stand-alone (non-collaborative) lateration algorithm, which estimates the initial position of each device using the GT coordinates of BLE anchors and the RSSI values measured. The last phase is dedicated to collaboratively estimating the position of the target device/user and combining it with the non-collaborative position estimated in the second phase. To this end, A) the collaborative devices exchange information between them (i.e., data of the first phase, position estimated in the second phase, and the BLE-RSSIs measured); B) the relative distance between devices is estimated based on a MLP ANNs model; C) a collaborative lateration algorithm is used to collaboratively estimate the device's position based on the relative distance estimated and the initial position of each device estimated in the second phase, and D) a midpoint line algorithm is used to combine the non-collaborative position estimated in the second phase with the position estimated collaboratively.

Regarding the evaluation, our proposed mobile device-based CIPS using MLP ANNs was tested in an office scenario and compared with a lateration baseline considering three configurations (configurations 1, 4, and 5 in Figure 5.3(a)), which correspond to short, medium, and large distances between collaborative devices distributed in each configuration, respectively. The previously listed challenging environment conditions are part of the office scenario, which generates a significant decrement of positioning accuracy in approaches based on RSSI. As it can be seen from Table 5.5, our proposed collaborative approach performs better than the lateration baseline in all the evaluation metrics of all the configurations (configurations 1, 4, and 5) evaluated. Specifically, in configuration 1 (short distances ≤ 4 m), configuration 4 (4 m $<$ medium distances ≤ 8 m), and configuration 5 (large distances $>$ 8 m) the maximum difference are 49.15 %, 19.24 %, and 21.48 % for the "median" metric, respectively. Moreover, considering the relative difference of the "RMSE", "mean" and "75th percentile" metric, we can observe that our proposed collaborative approach significantly outperforms the lateration baseline in configuration 1 (short distances), moderately outperforms the lateration baseline in configuration 4 (medium distances) and a little less in configuration 5 (large distances).We can observe the same behavior in Figure 5.5, which shows the ECDF plots of each configuration. The ECDF plot of configuration 1 (Figure 5.5(a)) shows that our collaborative approach outperforms the lateration baseline in all the cases. The ECDF plot of configuration 4 (Figure 5.5(b)) shows that our proposed approach outperforms the lateration baseline, but after 70 % of the cases, the positioning error of our approach begins to be close to that of lateration baseline. The ECDF plot of configuration 5 (Figure 5.5(c)) shows that within the first 80 % of cases, our proposed approach outperforms the lateration baseline. Nevertheless, in the first 40 % of cases, the positioning error of our approach is close to that of lateration baseline. Also, from 80 % to 90 % the lateration baseline outperforms our collaborative approach.

It should be pointed out that the lateration baseline's positioning accuracy was drastically reduced when compared to BLE–RSSI presented in the literature (2 m to 3 m error [6, 205]), due to the unfavorable test scenario conditions (i.e., hardware heterogeneity, strong NLOS and unstable signal strength conditions and the poor amount and inappropriate distribution of BLE anchors), which are however a reality in real-world scenarios. Nevertheless, the error values obtained are consistent with scenarios that take the low-density anchors' deployment issues into account. For instance, Cengiz [201] reported a mean position accuracy of 7.5 m in their lateration algorithm, which was evaluated in a scenario with 24 m by 24 m area and 8 anchors.

In general, the results demonstrated the feasibility and advantages of our mobile device-based CIPS using MLP ANNs to surpass the positioning accuracy of the conventional lateration baseline under the aforementioned challenging circumstances. Our approach decreases its positioning accuracy as the distance between collaborative devices in the configuration increases. While the magnitude of improvement obtained with our proposed CIPS (as shown in Table 5.5) may vary depending on the specific experimental conditions in other scenarios, the trend of accuracy achieved by the different device configurations (for the short, medium, and large distance between devices) can remain consistent for similar setups. Additionally, the results demonstrated the suitability of the MLP ANNs model for modeling the propagation of signals over short distances, while taking into account the unique properties of each receiving device and under NLOS conditions, which is crucial for determining the distance between (heterogeneous) collaborative devices under real-world conditions.

5.3 Hybrid collaborative approach for BLE–Wi-Fi RSSI fingerprinting

In accordance with the main findings and recommendations reported in our systematic review (Chapter 2), the most suitable technologies for CIPSs are BLE and Wi-Fi in combination with techniques that rely on RSSI and fingerprinting. Although there are technologies with better positioning accuracy (i.e., 5G, Ultra-wide band (UWB), and Visible Light Communication (VLC)), other factors are considered in the development of CIPS for human use, namely, the ubiquity of technologies in both, mobile devices and indoor environments, low-cost deployment, and low energy consumption, which can be provided by the BLE and Wi-Fi technologies. Wi-Fi technology, like BLE technology, was primarily designed to provide wireless communication among electronic devices [206] and has positioning limitations due to fluctuations in signal propagation mainly caused by obstacles and environmental geometries, which alter the measurements of the RSSI values and decrease the positioning accuracy. However, approaches based on fingerprinting provide a more accurate position but require complex implementation and long-term maintenance of their infrastructure increasing the cost and making them not accessible for a wide range of applications [207, 208].

In this section, we focus on enhancing the positioning accuracy of traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting. So, we propose a new variant of mobile device-based CIPS using MLP ANNs based on our CIPS baseline scheme presented in Section 5.1. The following sections detail its phases and main parts. Also, the performance of our approach and traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting approaches are compared and evaluated considering two real-world scenarios, and their main results are presented and discussed.

The main contributions are:

- We propose a variant of mobile device-based CIPS using MLP ANNs model proposed in Section 5.2 to enhance the positioning accuracy of traditional IPSs based on BLE–fingerprinting–k-NN and Wi-Fi–fingerprinting–k-NN methods.
- We demonstrate through the development and evaluation of our CIPS the usefulness of the CIPS baseline scheme proposed in Section 5.1.
- We experimentally evaluate and demonstrate the generalization of our pro-

posed variant of CIPS based on MLP ANNs model to enhance the positioning accuracy under different indoor environment conditions (i.e., office and lobby scenarios) and technologies (i.e., BLE and Wi-Fi).

- We experimentally demonstrate that our proposed variant of mobile device-based CIPS using MLP ANNs outperforms the traditional IPSs based on BLE–fingerprinting–*k*-NN and Wi-Fi–fingerprinting–*k*-NN methods when the collaborative devices have short and medium distances between them.

5.3.1 First phase: calibration phase

The first phase of our proposed CIPS is identical to the first phase described in Section 5.2.1.

5.3.2 Second phase: non-collaborative phase

In our second phase, unlike the stand-alone BLE-RSSI lateration method implemented in Section 5.2.2, we implement a stand-alone fingerprinting-*k*-NN method for Wi-Fi and BLE technologies.

Our stand-alone fingerprinting–*k*-NN method is described by the Algorithm 4 and based on the *k*-NN algorithm used in [172]. Its workflow is as follows:

- **1st step:** Gather the RSSI from BLE anchors/Wi-Fi APs ($RSSI_{RX}(TX)$) during a time window (tw) of $10\,\mathrm{s}$, excluding those that do not are part of the fingerprinting radio map (input data for Algorithm 4);
- **2nd step:** Group the RSSI, gathering in **1st step**, by BLE anchor/Wi-Fi AP, (line 1 in Algorithm 4);
- **3rd step:** Average the RSSI value per BLE anchor/Wi-Fi AP by applying the average operator to the RSSI values in each group. (line 2 in Algorithm 4);
- **4rd step:** Create a row vector with the averaged values ($\mathbf{FP}_{row} = [RSSI_{AP1}, \ldots, RSSI_{APm}]$) considering the length and elements' order of the fingerprinting radio map rows. The missing elements in the row vector are replaced with a positive value (i.e., 100). (line 3 in Algorithm 4);
- **5th step:** Compute the euclidean distance between $\mathbf{FP}_{row}$ and each of the i row of the fingerprinting radio map ($FPradiomap$) to obtain a euclidean distance

vector ($Euclidean_d$). (lines 4–6 in Algorithm 4);

- **6th step:** Arrange the fingerprinting radio map rows' index based on the sorting euclidean distance vector ($Euclidean_d$) values in ascending order. (line 7 in Algorithm 4);
- **7th step:** Select the (x,y) coordinates, stored in the fingerprinting radio map, corresponding to the first k rows' index. (line 8 in Algorithm 4);
- **8th step:** Estimate the position of the device/user ($\hat{\mathbf{P}}^{FP}(RX)$) by applying the centroid algorithm, which use the (x,y) coordinates selected in the **7th step.** (line 9 in Algorithm 4), and
- **9th step:** Share the estimated position, $\hat{\mathbf{P}}^{FP}(RX) = [\hat{P}_x^{FP}(RX), \hat{P}_y^{FP}(RX)]$.

The fingerprint radio map ($FPradiomap$), used as input, contains the information of the $RSSI$ values and the (x, y) coordinates where they were gathered. In the k-NN algorithm, we considered $k = 5$.

Algorithm 4 Stand-alone fingerprinting-KNN

Input: Information collected, within a time window tw, from the BLE anchors/Wi-Fi APs available: $RSSI_{RX}(TX)$ values
Input: k value
Input: $FPradiomap$: (x,y) coordinates and $RSSI_{radiomap}(TX)$ values
Output: Estimated device/user position $\hat{\mathbf{P}}^{FP}(RX) = [\hat{P}_x^{FP}(RX), \hat{P}_y^{FP}(RX)]$

1: Group the $RSSI_{RX}(TX)$ values by BLE anchor/Wi-Fi AP
2: Average $RSSI_{RX}(TX)$ values of each group : $\overline{RSSI_{RX}(TX)}$
3: Create a row vector with the averaged elements and match its length and element's order with the $FPradiomap$ rows. Missing elements are replaced with a positive value (i.e., 100): $\mathbf{FP}_{row} = [RSSI_{AP1}, \ldots, RSSI_{APm}]$
4: **for** $i \leftarrow 1$ **to** rows size of $FPradiomap$ **do**
5:     Compute the euclidean distance between $\mathbf{FP}_{row}$ and $FPradiomap\ row(i)$: $Euclidean_d(i)$
6: **end for**
7: Arrange the $FPradiomap$ rows' index based on the sorting $Euclidean_d$ values in ascending order.
8: Select the (x,y) coordinates corresponding to the first k rows' index
9: Estimate the device/user position ($\hat{\mathbf{P}}^{FP}(RX)$) applying the centroid algorithm, which uses the (x,y) coordinates values.
10: **Share the estimated device/user position** ($\hat{\mathbf{P}}^{FP}(RX) = [\hat{P}_x^{FP}(RX), \hat{P}_y^{FP}(RX)]$)

5.3.3 Third phase: collaborative phase

In our third phase, we re-use three of the four parts of the third phase implemented in Section 5.2.3, namely the information exchange between devices (part A, Section 5.2.3.1), collaborative lateration algorithm (part C, Section 5.2.3.3) and the algorithm that combines the estimated position in the non-collaborative and collaborative phases (part D, Section 5.2.3.4). Although for part B the MLP1 architecture with a single hidden layer proposed in Section 5.2.3 presents a similar performance in terms of RMSE for the office scenario, in the lobby scenario, its performance decreases. So, for part B, we designed a new MLP ANNs model to estimate the relative distance between devices. Our new model presents a different architecture with respect to the MLP ANNs model proposed in Section 5.2.3 to cope with diverse scenarios (i.e., office and lobby), technologies (i.e., BLE and Wi-Fi) and fingerprinting-based methods instead of lateration. In detail, the architecture consists of one input layer, three hidden layers, and one output layer. The input layer has six neurons, the first hidden layer has three neurons, and the second and third layers have fourteen neurons each. We used the hyperbolic tangent sigmoid (tangsig) activation function, the conjugate gradient backpropagation (trainscg) training function, and 25 and 12 epochs for the office and lobby scenarios, respectively.

Figure 5.6 shows the proposed MLP ANNs model architecture. The six features used in the input are: the $RSSI_{RX}(TX)$; the estimated position coordinates x ($\hat{P}_x^{FP}(TX)$) and y ($\hat{P}_y^{FP}(TX)$) of the transmitter (neighbor device/user), which were estimated by the stand-alone fingerprinting–k-NN algorithm (Algorithm 4); the estimated position coordinates x ($\hat{P}_x^{FP}(RX)$) and y ($\hat{P}_y^{FP}(RX)$) of the receiver (target device/user), which were estimated by the stand-alone fingerprinting–k-NN algorithm too; and the $RSSI_{RX}^{1m}(BX)$ (see Table 5.1 and Table 5.7 for the office and lobby scenarios, respectively).

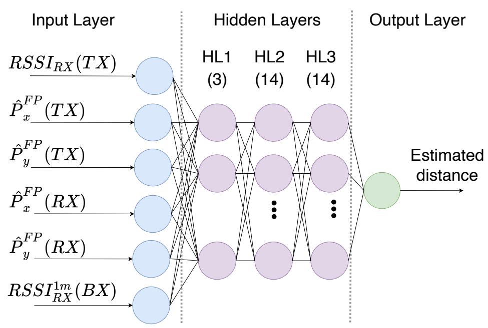


Figure 5.6 MLP neural network model architecture (fingerprinting). Used to estimate the relative pairwise distance between the target and neighboring devices/users.

The full collaborative positioning algorithm is based on the algorithm 3 described in Section 5.2.3.5. In order to re-use the algorithm, the following considerations must be taken into account:

- Instead of using the position of each collaborative device/user estimated by the stand-alone lateration ($\hat{P}_x^{Lat_1}(TX)$, $\hat{P}_y^{Lat_1}(TX)$, $\hat{P}_x^{Lat_1}(RX)$, $\hat{P}_y^{Lat_1}(RX)$) as input, we use the position estimated by the stand-alone fingerprinting–k-NN method ($\hat{P}_x^{FP}(TX)$, $\hat{P}_y^{FP}(TX)$, $\hat{P}_x^{FP}(RX)$, $\hat{P}_y^{FP}(RX)$), computed in the second phase (Section 5.3.2).
- To compute the final estimated position of the device/user ($\hat{\hat{\mathbf{P}}}(RX)$) using the formulas expressed in Eq. (5.2) and Eq. (5.3) (part D, Section 5.2.3.4), instead of considering the estimated stand-alone position $\hat{\mathbf{P}}^{lat_1}(RX)$, we consider the $\hat{\mathbf{P}}^{FP}(RX)$ computed by the stand-alone fingerprinting–k-NN (second phase, Section 5.3.2) and instead of naming the collaborative estimated position as $\hat{\mathbf{P}}^{lat_2}(RX)$, we renamed as $\hat{\mathbf{P}}^{lat_1}(RX)$ to keep the coherence of the variables names because in Section 5.3 the stand-alone devices' position is not estimated by lateration, only the collaborative estimated position is computed by the collaboratively lateration algorithm in part C.

5.3.4 Experiments and results

5.3.4.1 Experimental setup

This section enlists the main objectives and describes the setup of the experiments conducted to validate and test our proposed variant of mobile device-based CIPS using MLP ANNs with respect to stand-alone IPSs (i.e., BLE fingerprinting and Wi-Fi fingerprinting). The aims of the experiments are:

- To demonstrate the usefulness of the CIPS baseline scheme (presented in Section 5.1) to develop and test CIPSs that enhance the performance of stand-alone IPSs.
- To assess the feasibility of our proposed variant of CIPS to enhance the positioning accuracy of stand-alone IPSs (i.e., BLE fingerprinting and Wi-Fi fingerprinting).
- To evaluate the generalization of our CIPS based on MLP ANNs to work under different indoor scenarios conditions (i.e., office and lobby scenarios conditions) and technologies (i.e., BLE and Wi-Fi).
- To study the effect that the distance and NLOS conditions between collabo-

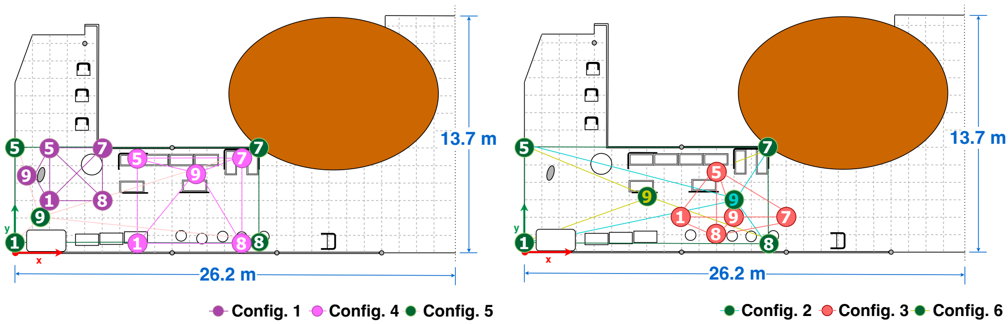
rative devices have on the positioning accuracy of CIPS.

We selected two real-world scenarios, office and lobby scenarios, to perform the data collection and experimentally test the stand-alone IPSs and CIPS proposed. The office scenario, located at Universitat Jaume I, Spain, is described in Section 3.2.2 and its 3D representation is shown in Figure 3.3(b). The same office scenario is used in the experiments of Section 5.2. The lobby scenario, located at Tampere University, Finland, is described in Section 3.5.1 and its 3D representation is shown in Figure 3.9.

In each scenario, we designed six collaborative configurations made up of five mobile devices. Each configuration presents a diverse distribution of mobile devices in the scenario, which provides different distances between devices and NLOS conditions. The collaborative data collection (broadcast and record data from neighboring devices) was carried out for 2 hours in each scenario. Also, simultaneously, the data from the deployed BLE anchors in the office scenario and Wi-Fi APs available in the lobby scenario were recorded. It should be pointed out that the version and frequency related to the Wi-Fi collected in the scenario are not available as the access points used were those available in the particular scenario and the software installed in the smartphones does not register such information. In detail, the collaborative data collection procedure for both, office and lobby scenarios, is in accordance with the described in Section 3.2.4 (Subset-C) and Section 3.5.1 respectively. Figure 5.3 present the distribution of mobile devices in the office scenario for each configuration and Figure 5.7 the distribution of mobile devices in the lobby scenario. In both scenarios, configurations 1, 4, and 5 are dedicated for testing (see Figure 5.3(**a**)) and Figure 5.7 (**a**)), and the configurations 3, 6, and 7 (see Figure 5.3(**b**)) and the configurations 2, 3 and 6 (see Figure 5.7 (**b**)) are dedicated for training and evaluation in the office and lobby scenarios, respectively. Table 5.2 and Table 5.6 summarize the position of devices GT coordinates in each scenario.

Table 5.6 Devices' Ground truth in each configuration in the lobby scenario.

ID/RX	Ground truth (m)														Scenario
	Config. 1		Config. 2		Config. 3		Config. 4		Config. 5		Config. 6		Config. 7		
	x	y	x	y	x	y	x	y	x	y	x	y	x	y	
1	2	3	0	0.5	9	2	6	0.5	0	0.5	0	0.5	-	-	Lobby
5	2	6	0	6	11	4.5	6	5.5	0	6	0	6	-	-	Lobby
7	5	3	14	6	15	2	12	5.5	14	6	14	6	-	-	Lobby
8	5	6	14	0.5	11	1	12	0.5	14	0.5	14	0.5	-	-	Lobby
9	1	4.5	12	3	12	2	9.5	4.5	1.5	2	7	3	-	-	Lobby



(a) Configurations 1, 4, and 5 used in the testing

(b) Configurations 2, 3, and 6 used in the training & evaluation

Figure 5.7 Distribution of the configurations used in the training & evaluation and testing in the lobby scenario.

Regarding the hardware, we used a total of nine mobile devices to perform the experiments in the scenarios. Devices 1, 2, 3, 4, and 6 for the office and 1, 5, 7, 8, and 9 for the lobby scenario. Each device is able to measure the RSSI of neighboring collaborative devices and to transmit BLE packets using the iBeacon protocol. Also, they are able to measure the RSSI of Wi-Fi APs available in the lobby and the RSSI of deployed BLE anchors in the office scenario. Further information about the devices, as well as the $RSSI_{RX}^{1m}$ values corresponding to each of them used in the experiments, is provided in Table 5.1 and Table 5.7 for the office and lobby scenarios, respectively.

Table 5.7 $RSSI_{RX}^{1m}(BX)$ values by device (lobby scenario).

ID/RX	Device name	Model	$RSSI_{RX}^{1m}(BX)$ values (dBm)	Scenario
1	Galaxy S8	SM-G950F	-68.88	Lobby
5	Honor 20 Lite	HRY-LX1T	-62.11	Lobby
7	Galaxy S6 Edge	SM-G928F	-61.17	Lobby
8	Huawei P40 Lite	CDY-NX9A	-69.74	Lobby
9	Galaxy A12	SM-A125F	-66.79	Lobby

The stand-alone fingerprinting–k-NN approach is implemented in two sequential phases. The first phase is a training phase, where surrounded RSSIs are measured on reference points of the scenario to create a database of RSSI-signatures (radio map) [209, 210]. The second phase, known as the operational or online phase, is devoted to estimating the unknown position based on the comparison between the created radio map and the signatures measured on the unknown position [209].

For the experiments conducted in the office scenario, we created a radio map based on the BLE anchors deployed in the environment. This BLE radio map considers five BLE anchors (red points 1, 4, 9, 18, and 19 in Figure 3.12 (**a**)) deployed in the office scenario and 72 reference points (blue points) marked on the floor as shown in Figure 3.12 (**a**). Eleven samples by reference point were collected and saved. In total, the BLE radio map contains 792 samples.

For the experiments conducted in the lobby scenario, we created a radio map based on the opportunistic Wi-Fi signals present in the lobby scenario. This Wi-Fi radio map considers the 67 Wi-Fi APs presents in the lobby scenario and 136 reference points marked on the floor as shown in Figure 3.13. In each reference point, eight samples were collected and saved. In total, the Wi-Fi radio map contains 1088 samples.

5.3.4.2 Tuning the Multilayer Perceptron (MLP) neural network

To define the most suitable MLP architecture and its hyperparameters for the models used in the office and lobby scenario, we evaluate four architectures in each scenario. The hyperparameters considered were the number of hidden layers (1 to 3) and the number of hidden neurons. We use as a reference for the tunning of our MLP neural network the results of the evaluation conducted in Section5.2.4.2. Specifically, the parameters of the MLP1, which presented the most accurate relative distance estimation in the office scenario, namely the number of neurons in the first layer (3), the hyperbolic tangent sigmoid (tansig) activation function, and a scaled conjugate gradient backpropagation training function (trainscg). Then, based on the initial results of the MLP neural network architecture in both scenarios, we consider 3 architectures, one with 2 hidden layers and two with 3 hidden layers, to improve the results. The hyperparameters set up for each architecture are detailed in Table 5.8.

The results of comparing the real distance with the estimated distance in each of the 4 neural network architectures MLP are presented in Figure 5.8 (office scenario) and Figure 5.9 (lobby scenario) through density scatter plots, as well as their correlation coefficient (R), and the RMSE.

Analyzing the results of Figure 5.8 (office scenario), we can observe that the correlation coefficient (R) of the three hidden layers MLP architectures (MLP2 and MLP3) is greater than the one hidden layer (MLP1). Considering the three hidden

Table 5.8 Tested MLP architectures and hyperparameters for office and lobby scenarios.

Parameters	MLP1	MLP2	MLP3	MLP4
No. Input layers	1	1	1	1
No. Hidden layers (HLs)	1	2	3	3
No. Output Layer	1	1	1	1
No. Neurons HL1	3	3	3	3
No. Neurons HL2	-	6	6	14
No. Neurons HL3	-	-	6	14
Training function	trainscg			
Activation function	tansig			
Performance function	Mean Square error			

layers MLP architectures (MLP3 and MLP4), we can notice that a higher number of neurons in the second and third layers (i.e., 14 neurons) increase the correlation coefficient and reduce the RMSE. Comparing the density scatter plots of MLP3 and MLP4 through illustrated in Figure 5.4 (c) and (d), respectively, we notice that the MLP architecture with a higher number of neurons in the second and third layers (MLP4) has a higher density of predicted values near to the real values than the one with the lower number of neurons in the second and third layers (MLP3). Regarding the results of Figure 5.9 (lobby scenario), we observe that in the four MLP architectures (MLP1 – MLP4) the predicted values near the real values are no so dense as the presented in Figure 5.8, which is also indicated by the low value of the correlation coefficient. However, similar to the evaluation of MLP architecture with the training dataset of the office scenario, the MLP architecture with a greater number of neurons in the second and third layers (MLP4) presents the highest value of the correlation coefficient and the lowest value of RMSE in comparison with MLP1, MLP2, and MLP3.

It should be noted that the MLP1 architecture with a single hidden layer (Figure 5.8 (a)), evaluated in the office scenario, presents similar values to those of the architecture selected in Section 5.2.4.2 (MLP1) for the same scenario. However, for the lobby scenario, the value of the correlation coefficient is lower, and the RMSE is slightly higher in comparison with the MLP1 of Section 5.2.4.2. Consequently, in terms of accuracy and correlation coefficient, the MLP4 with three hidden layers (3, 14, and 14 neurons for the first, second, and third layer, respectively), a hyperbolic tangent sigmoid activation function, and a scaled conjugate gradient backpropagation training function are better able to estimate the relative distance using BLE–RSSI

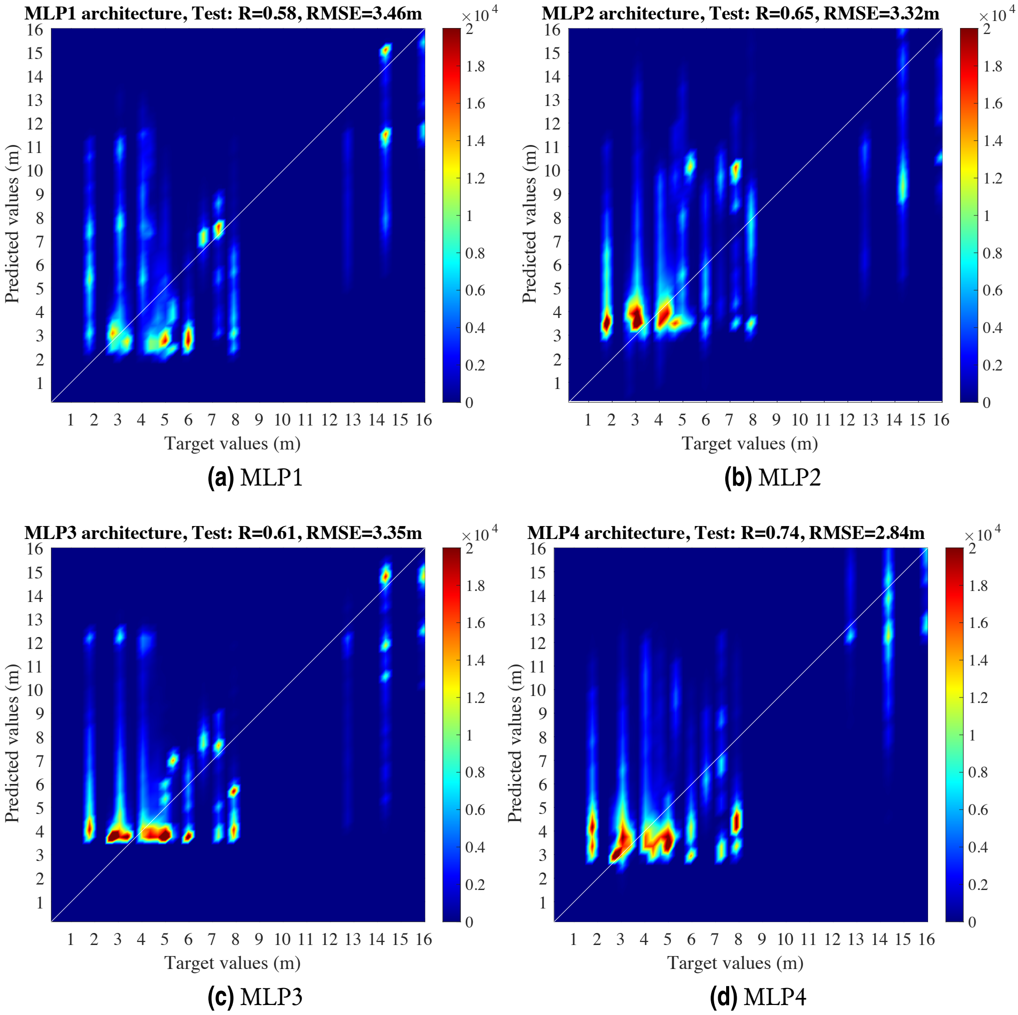
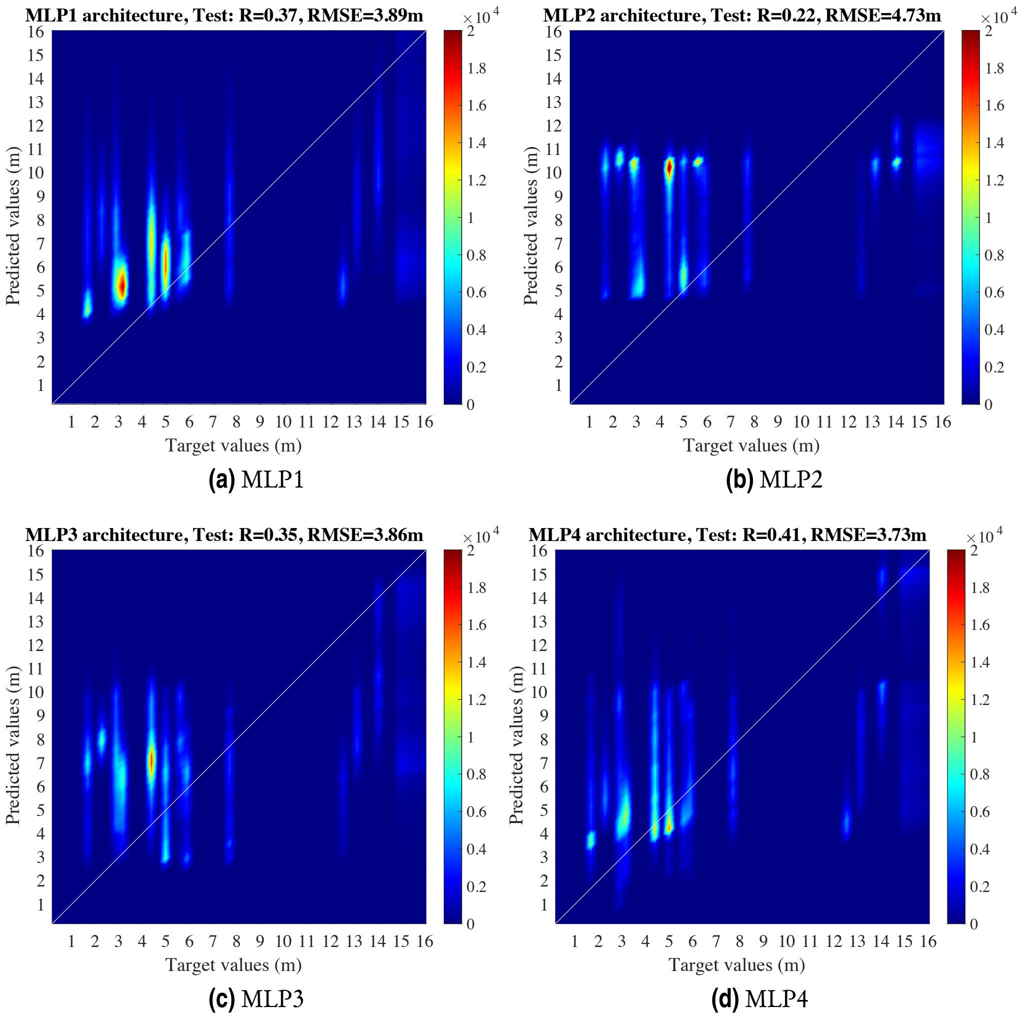


Figure 5.8 Target vs Predicted distances from the test dataset estimated with MLP1–MLP4 architectures (Office scenario–BLE-fingerprinting).

data in both office and lobby scenarios.

5.3.4.3 Results of the collaborative model

The main results of the evaluation of our proposed CIPS using MLP ANNs and the stand-alone fingerprinting–k-NN approach are presented in this section. Table 5.9 and Figure 5.10 present the office scenario's results and Table 5.10 and Figure 5.11 the lobby scenario's results. Also, we present the results divided by configuration



(a) MLP1 **(b)** MLP2 **(c)** MLP3 **(d)** MLP4

Figure 5.9 Target vs Predicted distances from the test dataset estimated with MLP1–MLP4 architectures (Lobby scenario–Wi-Fi-fingerprinting).

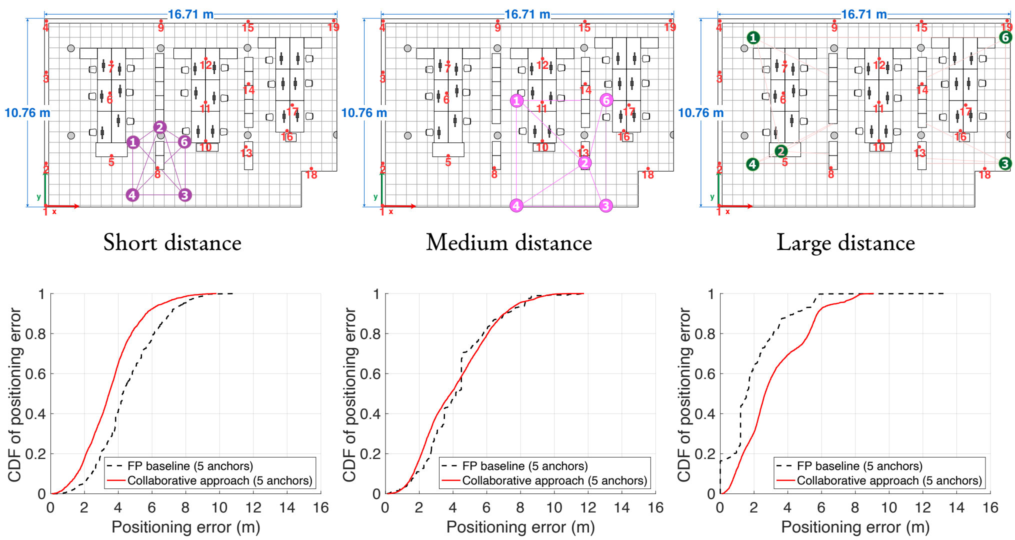
to show the effect of the relative distance between collaborative devices and NLOS conditions on positioning accuracy in CIPS.

Table 5.9 summarizes the results of the evaluation of the CIPS using MLP ANNs, and the stand-alone fingerprinting–k-NN approach, which considered a reduced number of BLE anchors (i.e., anchors 1, 4, 9, 18, and 19 in Figure 5.3(**a**)) in the office scenario. The Table 5.9 presents the evaluation metrics RMSE, mean, median, 75th and 90th percentile, and the relative difference of configurations 1, 4, and 5 of both approaches.

Table 5.9 Main results metrics provided by the BLE fingerprinting baseline and our proposed collaborative approach.

	BLE fingerprinting baseline			Collaborative approach					
	Error (m)			Error (m)			Diff		
Eval. metric	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5
RMSE	4.92	4.7	2.54	3.91	4.64	3.72	↓ 20.53%	↓ 1.28%	↑ 46.46%
Mean	4.58	4.25	1.96	3.55	4.12	3.16	↓ 22.49%	↓ 3.06%	↑ 61.22%
Median	4.25	4.16	1.53	3.45	3.86	2.65	↓ 18.82%	↓ 7.21%	↑ 61.22%
75^{th} percentile	5.81	5.31	2.68	4.45	5.67	4.86	↓ 23.41%	↑ 6.78%	↑ 73.20%
90^{th} percentile	7.14	6.97	4.34	5.64	7.06	5.75	↓ 21.01%	↑ 1.29%	↑ 32.49%

Figure 5.10 shows the devices' distribution of the three configurations set in the office scenario. The configurations present different relative distances between devices, namely short distance (configuration 1), medium distance (configuration 4), and large distance (configuration 5). Also, the ECDF plots of each configuration are presented. The red lines represent the results for CIPS using MLP ANNs and black dashed lines for the stand-alone fingerprinting–k-NN approach.



(a) Configuration 1 **(b)** Configuration 4 **(c)** Configuration 5

Figure 5.10 CDF of the fingerprinting baseline and collaborative approach (5 BLE anchors) of configurations 1, 4, and 5 in the office scenario.

Table 5.10 summarizes the results of the evaluation of the CIPS using MLP ANNs, and the stand-alone fingerprinting–k-NN approach, which considered the

Wi-Fi APs available in the lobby scenario. The evaluation metrics used are the same that in Table 5.9.

Table 5.10 Main results metrics provided by the Wi-Fi fingerprinting baseline and our proposed collaborative approach.

	Wi-Fi fingerprinting baseline			Collaborative approach					
	Error (m)			Error (m)			Diff		
Eval. metric	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5	Config. 1	Config. 4	Config. 5
RMSE	5.83	4.04	5.4	5.37	4.1	6.19	↓ 7.89%	↑ 1.49%	↑ 14.63%
Mean	5.2	3.51	4.86	5	3.68	5.89	↓ 3.85%	↑ 4.84%	↑ 21.19%
Median	4.74	3.18	4.34	5.12	3.59	5.79	↑ 8.02%	↑ 12.89%	↑ 33.41%
75^{th} percentile	7.13	4.62	5.68	6.29	4.92	7.12	↓ 11.78%	↑ 6.49%	↑ 25.35%
90^{th} percentile	9.3	6.25	7.88	7.49	5.88	8.2	↓ 19.49%	↓ 5.92%	↑ 4.06%

Figure 5.11 shows the devices' distribution of the three configurations set in the lobby scenario and their ECDF plots. Similarly that in Figure 5.10, configurations 1, 4, and 5 represent short, medium, and large relative distance between devices, respectively. Black dashed lines and red lines in the plots represent the stand-alone and collaborative approaches, respectively.

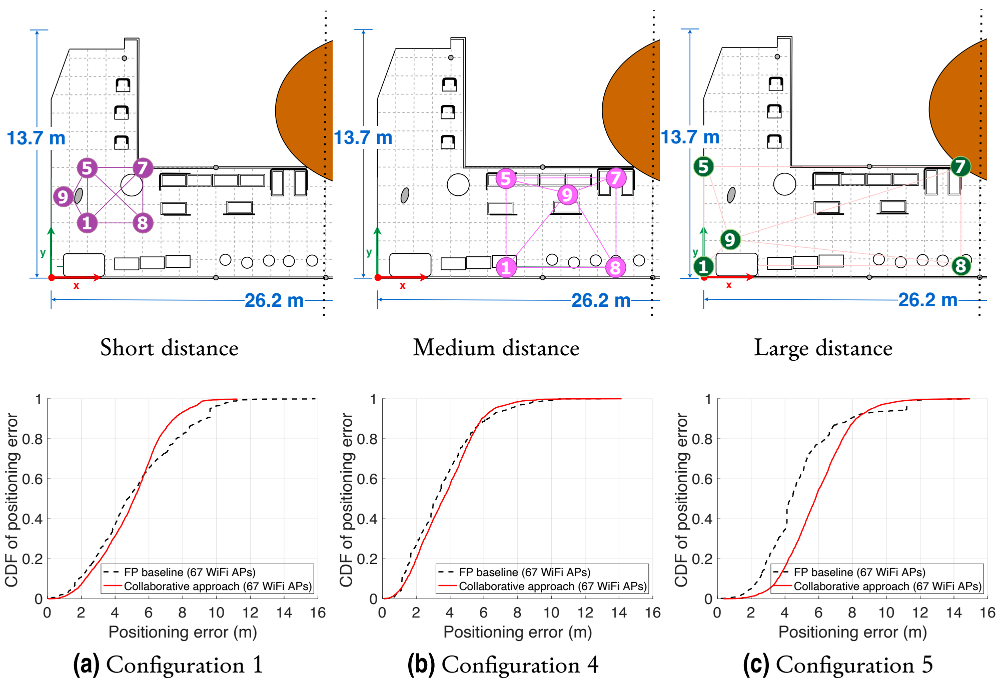


Figure 5.11 CDF of the fingerprinting baseline and collaborative approach (67 Wi-Fi APs) of configurations 1, 4, and 5 in the lobby scenario.

5.3.5 Discussion

We proposed a variant of mobile device-based CIPS using MLP ANNs to enhance the positioning accuracy of traditional BLE and Wi-Fi fingerprinting IPSs. The system's structure is based on our proposed CIPS baseline scheme described in Section 5.1. We experimentally test the proposed collaborative approach in two real-world indoor scenarios (i.e., office and lobby). In those scenarios, we consider various distributions of different collaborative mobile devices (configurations) and technologies (Wi-Fi and BLE) to evaluate the generalization and positioning accuracy of our approach. In each scenario, we distributed the mobile devices considering three distances between them, namely short, medium, and large distances for configurations 1, 4, and 5, respectively. The different distances allow us to study their effect on the positioning accuracy of CIPS.

The office scenario's results presented in Section 5.3.4.3 (Table 5.9 and Figure 5.10) show that our collaborative approach outperforms the stand-alone one when the mobile devices are very near to each other (configuration 1). Specifically, Table 5.9 shows that in configuration 1, our collaborative approach reduced the error in all the evaluation metrics. The maximum difference is 23.41% for the "75th percentile" metric. Under the shortest distance between collaborative devices (transmitters and receivers), the signal propagation presents less attenuation and reduced multipath propagation. Similarly, in the medium distance (configuration 4), we can notice from the ECDF of Figure 5.10(b) that our approach in the first 60% and after the 90% of cases outperform the stand-alone, also provides a most stable position estimation. As the devices are more distant from each other, the physical obstruction and multipath propagation due to surrounding objects are more frequent (see the sketches in Figure 5.10). It causes a decrease in the accuracy of the estimated relative distance between the devices and the system's overall accuracy. Nevertheless, our approach, thanks to its MLP ANNs model used for estimating relative distance, can partially mitigate some of those effects in the medium distance. In the large distance case (configuration 5), we can observe from the ECDF of Figure 5.10(c) that our approach performance is worse than the stand-alone. Additionally, from Table 5.9, we notice that in configuration 5, the stand-alone in all its evaluation metrics reduced by around 50% the error in comparison with their other configurations. The cause is that in configuration 5, the collaborative devices are closer to the BLE anchors (i.e., anchors 1, 4, 9, 18, and 19 in Figure 5.3(a)) used for creating the BLE radio map. So, the high improvement of positioning accuracy of the stand-alone approach, together with the large distance, contributes to increasing the difference between the collaborative and stand-alone approach results in configuration 5.

The lobby scenario's results presented in Section 5.3.4.3 (Table 5.10 and Figure 5.11) show that our collaborative approach in the short distance case (configuration 1) outperform the stand-alone approach. Unlike the office scenario, its performance is more moderate, reducing the error in four of five evaluation metrics, as it can be seen in Table 5.10. In the medium distance (configuration 4), from the ECDF of Figure Figure 5.11(b), we observe that until the 80% of cases, the stand-alone approach outperform the collaborative one, but in the remaining cases, the collaborative approach outperforms the stand-alone. In the large distance case (configuration 5), we notice from the ECDF of Figure 5.11(c) that our approach after the 90% of cases moderate outperform the stand-alone approach. However, in the rest of the cases, its performance is worse than the stand-alone. Even though in the lobby scenario, the distance between the collaborative devices of the configurations is similar to that of the office scenario and our CIPS is the same, the environment geometry, scenario's area, the mobile devices (see Table5.1 and Table 5.7 for the office and lobby scenarios, respectively), and technology used (Wi-Fi instead of BLE) are different. Nevertheless, we can see that in the lobby scenario, the configurations with the shortest distance between collaborative devices present the best performance as in the office scenario. It should be noted that our proposed mobile device-based CIPS using MLP ANNs improved positioning accuracy in both experiments independently that the scenarios, technologies, and mobile devices were different. Also, based on the results, we can mention that its usability and performance can be exploited in cases with a high density of collaborative users/devices in the environment.

To sump up, the main results of the evaluation of our proposed variant of mobile device-based CIPS using MLP ANNs demonstrated that CIPS enhances the positioning accuracy of traditional fingerprinting IPSs under specific conditions. Mainly, conditions where the collaborative devices have short and medium distances between them. Moreover, the integration of MLP ANNs model in CIPSs allows us to use our approach under different scenarios and technologies, showing its level of generalization, usefulness, and feasibility.

5.4 Comparison with other collaborative methods

Finally, to assess how well our proposed CIPS variants perform in comparison with state-of-the-art (SOTA) CIPSs, we compare their accuracy to eight SOTA CIPSs. We selected these SOTAs CIPSs based on their mobile device orientation and similar evaluation metrics to our proposed CIPS, such as "mean", "90th percentile" and "RMSE". This made them suitable for a fair comparison. We not only considered the CIPSs that have been experimentally evaluated but also those evaluated through simulations. Simulations provide a controlled environment that can be more ideal than experimental conditions, allowing for a more comprehensive comparison of differences in accuracy. However, it is important to note that results based on simulations may not necessarily reflect real-world performance, and could potentially give a distorted picture of the results. To address this, we have clearly indicated which CIPSs were experimentally evaluated and which based on simulations.

Reproducing and replicating the existing SOTA models and their reported results is practically not feasible, as they may use specific technologies, settings, and/or infrastructure which are not available in our scenarios and collected datasets. Therefore, the comparison is based on published results, which provide a reasonable performance comparison benchmark. Specifically, the comparison focused on three aspects: first, the accuracy improvement compared to the non-collaborative baseline system; second, the test conditions, which included the homogeneity/heterogeneity of devices, LOS/NLOS environments, and the type of evaluation (experimental/simulated/hybrid); and third, the complexity of our proposed solutions compared to the SOTA CIPSs. To determine the complexity, we consider the number of parameters needed for the model and the size and type of model implemented.

Within the SOTA CIPSs tested experimentally, we have included the following:

- Taniuchi, Liu, Nakai, and Maekawa [97] proposed a CIPS based on a spring model and homogeneous smartphones using Wi-Fi-fingerprinting and BLE RSSI. Their system was tested through experiments and improved the "mean" accuracy within 2.7%-32.6% in several scenarios.
- Seco and Jiménez [118] proposed a particle filter approach for CIPS , which relied on smartphones with homogeneous Radio-Frequency Identification (RFID) tags attached to them. This system was tested through experiments, and the results showed an improvement of 9.09% for the "90th percentile".

- Ta, Dao, Vaufreydaz, and Castelli [138] introduced two CIPS versions based on particle filter and Wi-Fi and BLE RSSI values. The implemented versions were tested experimentally considering heterogeneous devices in LOS between them in a corridor scenario. The results showed an improvement of the “mean” accuracy within 5.3%-47.5%.
- Della Rosa, Wardana, Mayorga, Simone, Raynal, Figueiras, and Frattasi [74] presented a proof of concept of a collaborative mobile positioning approach for RSSI Wi-Fi using Extended Kalman Filter (EKF) and Non-Linear Least Square (NLLS). The positioning accuracy was tested experimentally considering LOS conditions between devices. The results showed an improvement of the “RMSE” accuracy within 35.22%-57.25%.
- Morral and Dieng [94] proposed a collaborative RSSI-based indoor positioning system based on Distributed Stochastic Approximation (DSA) algorithm, which refines the positioning accuracy of the nodes computed by a Biased-maximum Likelihood Estimator (B-MLE) algorithm. The system was tested on real indoor scenarios using TMote Sky and TinyOS CC2420 devices under NLOS conditions. The system improved the “mean” accuracy within 2.96%-44.6%.

Additionally, we included the following SOTA CIPSs tested through simulations or in a hybrid mode:

- Chen, Yang, and Wang [105] proposed a fingerprinting-based cooperative positioning method that used pairwise distances between peer users as a physical constraint and probabilistic peer selection to enhance mobile users’ position estimates. The authors conducted a hybrid test by estimating the initial positions of users with a real radio map and simulating multiple users with pairwise distances. The distance measurement model is based on the true distances with noise added. The results showed an improvement of the “90th percentile” within 54.78%-66.1% for this method.
- Noh, Yamaguchi, and Lee [41] presented an infrastructure-less CIPS, which uses collaborative peer-to-peer Wi-Fi beaconing and dead reckoning based on smartphones. The positioning accuracy of the general system was tested using commercial simulator software (Qualnet), and the radio propagation data was

generated by Wireless InSite software using the ray-tracing technique. The system improved the "mean" accuracy within 51.43%-51.56%.

- Vaghefi and Buehrer [111] proposed an algorithm for cooperatively tracking mobile nodes in NLOS environments based on semidefinite programming. The simulation results showed an improvement of 33.87% for the "90th percentile".

Our two CIPS variants utilize ANN to enhance positioning accuracy in real-world scenarios, taking into account the presence of heterogeneous mobile devices and NLOS conditions. Our experiments demonstrated a maximum improvement of 43.49%, 29.32%, and 38.72% in the "mean", the "90th percentile" and "RMSE", respectively, when compared to a baseline system.

Table 5.11 summarizes the reported results used in the comparison between the SOTA CIPSs and our proposed CIPSs.

Table 5.11 Comparison of SOTA CIPSs vs proposed CIPS

System Ref.	Eval. metric	Baseline error (m)	Collaborative error (m)	Diff. (%)	Test conditions				Device used			Complexity
					NLOS	LOS	Exp.	Sim.	Homog.	Het.	Type	
[97]	Mean	2.08 1.45	2.02 0.98	2.7 (Min.) 32.6 (Max.)	✓	–	✓	–	✓	–	Smartphones	○
[118]	90^{th} percentile	4.4	4	9.09	✓	–	✓	–	✓	–	Smartphones with RFID tags	◐
[138]	Mean	3.8 4	3.6 2.1	5.3 (Min.) 47.5 (Max.)	–	✓	✓	–	–	✓	Smartphones	◐
[74]	RMSE	3.35 3.77	2.17 1.61	35.22 (Min.) 57.25 (Max.)	–	✓	✓	–	✓	–	Laptops	◐
[94]	Mean	1.35 1.39	1.31 0.77	2.96 (Min.) 44.6 (Max.)	✓	–	✓	–	N/S	N/S	TMote Sky and TinyOS CC2420	●
*[105]	90^{th} percentile	1.57 0.59	0.71 0.2	54.78 (Min.) 66.1 (Max.)	–	✓	✓	✓	–	✓	Smartphones	○
*[41]	Mean	4.55 40.98	1.24 19.85	51.43(Min.) 51.56 (Max.)	✓	–	–	✓	N/S	N/S	Smartphones (DR part)	◐
*[111]	90^{th} percentile	6.2	4.1	33.87	✓	–	–	✓	N/A	N/A	N/A	●
CIPS proposed	Mean 90^{th} percentile RMSE	4.29 6.72 4.52	2.42 4.75 2.77	43.49 (Max.) 29.32 (Max.) 38.72 (Max.)	✓	–	✓	–	–	✓	Smartphones	◐

Note:
N/S: Not Specified; N/A: Not Applicable; Exp.: Experimental; Sim.: Simulated; Homog.: Homogeneous; Het.: Heterogeneous;
*: Systems tested through simulations or in a hybrid mode
and ○: Low; ◐: Medium ; and ●: High

Based on the SOTA CIPSs tested experimentally [97, 118, 138, 74, 94], we can observe that our proposed CIPS variants outperform the CIPS in [97] by 10.89% and that two CIPS ([138, 94]) slightly outperform our proposed CIPS variants by

4.01% and 1.11%, respectively, based on the maximum "mean" accuracy difference. Considering the maximum "90th percentile" accuracy difference, our proposed CIPSs variants outperform the CIPS in [118] by 20.23%. Regarding the maximum "RMSE" accuracy difference, the CIPS in [74] outperform our proposed variants by 18.53%. Qualifying the aforementioned results, we note that those CIPSs that outperformed our CIPS variants by more than 2% ([138, 74]) were all tested in LOS conditions. It is important to note that LOS conditions provide a direct path between the transmitter and receiver, which reduces variance and eases position estimation. On the other hand, the CIPS with similar or lower performance as our proposed variants ([97, 94, 118]) were tested in NLOS conditions, where obstacles may scatter the signal and therefore reduce accuracy. Considering the hardware used, we can notice that the superior performance achieved by the CIPS in [94] with respect to our proposed CIPSs may be attributed to the use of specific telecommunication boards. Moreover, due to the limited availability of heterogeneous device cases in the SOTA systems and their diverse test conditions, we can not conduct a precise comparison to evaluate the impact of homogeneous and heterogeneous devices on positioning accuracy.

The SOTA CIPSs in [41], [105] and [111], tested through simulation or hybrid mode and in NLOS conditions, slightly outperform our proposed CIPS variants by 8.07% in terms of maximum "mean", and by 36.78% and 4.55% considering the maximum "90th percentile" accuracy difference, respectively. On one hand, the evaluation of systems based on simulations allows for greater control and manipulation of factors that can impact the positioning accuracy, such as the number and placement of obstacles and devices, the signal-to-noise ratio, and the receiver sensitivity. For example, a greater density of collaborative devices can improve the positioning accuracy of CIPS. On the other hand, the experimental evaluation of the systems is prone to environmental and hardware limitations that can introduce uncertainty and variability in the results.

Regarding complexity, our proposed systems are comparable to CIPS in [138] and [74] based on particle filter and the CIPS in [74] based on EKF and NLLS. Nevertheless, the modularity of our system allows us their straightforward implementation and configuration. Moreover, compared with [118], our systems do not rely on additional hardware.

To sum up, our proposed CIPS variants demonstrate positioning accuracy improvements that are either better or similar to SOTA CIPSs under similar test conditions (i.e., NLOS conditions and tested experimentally). Although our CIPSs are experimentally tested, we obtained positioning accuracy improvements that are close to those reported by simulation-based systems. Also, the complexity of our proposed CIPSs is comparable with the SOTA CIPS included in the comparison.

5.5 Chapter summary and discussion

In this chapter, we proposed a versatile and straightforward CIPS baseline scheme designed for developing CIPSs capable of improving the performance of traditional IPSs. To this end, the modularity of our baseline scheme allows us to implement, evaluate and improve the performance of its modules and the collaborative indoor positioning technologies, techniques, and methods. Moreover, to validate and demonstrate the usefulness of our baseline scheme for enhancing the performance (i.e., position accuracy) of traditional IPSs, we developed and experimentally evaluated two variants of a mobile device-based CIPS using MLP ANNs model. In those developed CIPSs, we considered different technologies (i.e., Wi-Fi and BLE), techniques (i.e., lateration and fingerprinting), and two real-world scenarios.

The CIPS baseline scheme considered in its design the information presented in our CIPS systematic review, namely the concept of compatibility among CIPS, system modularity, architecture, and infrastructure. The considerations about technologies, techniques, and methods are explained further in the description of the two CIPS designed based on our baseline scheme. Our baseline scheme consists of a modular system, which provides versatility to be modified and implemented and facilitates compatibility with other CIPS modules designed under the same scheme. It also includes a decentralized architecture, which is able to distribute the computational load, reduce the data transfer among devices, and enable each device to use different technologies, techniques, and methods in the IPS. Regarding the infrastructure, the baseline scheme permits both infrastructure-based and infrastructure-free use.

Unlike most of the CIPSs analyzed in the systematic review that considers only one type of device, we considered using heterogeneous devices in our CIPSs. Therefore, we added one more phase to the two existing phases (collaborative and non-collaborative) to register the various devices used in the system. Our baseline scheme divides the system into 3 phases: the registration phase, which is used to register heterogeneous mobiles devices that interact in the CIPS; the non-collaborative phase, where each device independently estimates its initial position based on a IPS; and a collaborative phase, which collaboratively enhance the estimated position of the target device/user.

In the first variant of CIPS, presented in Section 5.2, we designed a mobile device-based CIPS using MLP ANNs to improve the positioning accuracy of BLE–RSSI lateration-based methods. In the system, we used the BLE technology and the lateration approach in both the non-collaborative and collaborative phases. In detail, our proposed CIPS faces three aspects that decrement the positioning accuracy in reduced the positioning error traditional lateration-based IPS without increasing the infrastructure cost. The first aspect is the NLOS conditions and deficient anchors deployment. Second, inefficient modeling of the signal propagation. Third, the effect of device heterogeneity on positioning accuracy. In our solution, in addition to using the surrounding mobile device to extend the positioning network, we proposed a novel model to estimate the relative distance between collaborative mobile devices based on the MLP ANNs model. Our approach uses the MLP ANNs model to replace the LDPL model. LDPL models mainly estimate the distance based on the signal attenuation formulas and a few parameter settings. Nevertheless, with the neural network model, the distance estimation is improved by considering the relation between distance and RSSI patterns, pairwise device position, identification of devices (transmitter and receiver), and variation of RSSI measurements due to the devices' hardware heterogeneity.

The evaluation of both, our proposed collaborative approach and the traditional lateration-based IPS was conducted in an office scenario. The scenario considers the diverse distributions of heterogeneous mobile devices (configurations) and the aspects that affect the positioning accuracy, mentioned before. The result of comparing both approaches demonstrated the feasibility and advantages of our approach to outperform the traditional lateration-based IPS under these challenging conditions. Considering the relative difference of the "RMSE", "mean" and "75th percentile" metric, we observed that our proposed collaborative approach significantly outperforms the lateration baseline in configuration 1 (short distances $\leq 4\,\mathrm{m}$), moderately outperforms the lateration baseline in configuration 4 ($4\,\mathrm{m} <$ medium distances $\leq 8\,\mathrm{m}$) and a little less in configuration 5 (large distances $> 8\,\mathrm{m}$).

Additionally, it should be pointed out the suitability of the MLP ANNs model for modeling the propagation of signals over short distances (see density scatter plot Figure 5.4(a)) while taking into account the unique properties of each receiving device and under NLOS conditions, which is crucial for determining the distance between (heterogeneous) collaborative devices in real applications.

In the second variant of CIPS, presented in Section 5.3, we designed a mobile device-based CIPS using MLP ANNs to enhance the positioning accuracy of IPSs based on fingerprinting approaches. Although we designed a similar system (same baseline scheme) in Section 5.2.3.2, the new proposed MLP ANNs model presents a different architecture, which enables the collaborative system to work under diverse scenarios (i.e., office and lobby) and technologies (i.e., BLE and Wi-Fi). Moreover, the new architecture is designed to process the input data provided by fingerprinting–*k*-NN instead of lateration methods of the non-collaborative phase.

We experimentally tested the proposed collaborative approach in two indoor scenarios (i.e., office and lobby). In those scenarios, we considered various distributions of different collaborative mobile devices (configurations), NLOS conditions, and in each scenario, a diverse technology (Wi-Fi and BLE) to evaluate the generalization and positioning accuracy of our approach. Moreover, we evaluated the effect of the distance between collaborative devices on the positioning accuracy of CIPSs. In the evaluation, we considered three different distances between the collaborative devices (short, medium, and large distance).

The results demonstrated that: for short distances between collaborating devices, our proposed approach outperforms the traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting with a maximum error reduction of 23.41% and 19.49% for the "75th percentile" and "90th percentile" metric, respectively. For medium distances, our proposed approach outperforms the traditional IPSs based on BLE–fingerprinting in the first 60% and after the 90% of cases in the ECDF and only partially (20% of cases in the ECDF) the traditional IPSs based on Wi-Fi–fingerprinting. For large distances, our proposed approach performance is worse than the traditional IPSs based on fingerprinting.

Additionally, we performed a literature-based comparison of our proposed CIPS variants with SOTA CIPSs. The results showed that our proposed systems achieve comparable or better accuracy than the SOTA systems, while using heterogeneous devices and NLOS conditions in the test scenarios. We also note that their complexity is comparable with the evaluated SOTA systems.

Overall, the results demonstrate the usefulness and usability of our CIPS baseline scheme to develop new CIPS considering different technologies (i.e., Wi-Fi and BLE) and techniques (i.e., lateration and fingerprinting) to improve the positioning accuracy of traditional IPSs, namely IPSs based on BLE–lateration, BLE–fingerprinting, and Wi-Fi–fingerprinting. Specifically, our first variant of mobile device-based CIPS using MLP ANNs proposed demonstrated that outperforms the positioning accuracy of the lateration baseline in all the configurations tested (i.e., where the collaborative devices have short, medium, and large distances between them), the second variant of mobile device-based CIPS using MLP ANNs demonstrated that CIPS enhances the positioning accuracy of traditional IPSs based on fingerprinting under specific conditions. Mainly, conditions where the collaborative devices have short and medium distances between them. Moreover, the integration of MLP ANNs model in CIPSs allows us to use our approach under different scenarios and technologies, showing its level of generalization, usefulness, and feasibility.

6 CONCLUSIONS

The research of this doctoral thesis focused on the development and evaluation of mobile device-based collaborative indoor techniques, using Multilayer Perceptron (MLP) Artificial Neural Networks (ANNs), for human positioning to enhance the position accuracy of traditional Indoor Positioning Systems (IPSs) based on Received Signal Strength Indicator (RSSI).

As an initial step of our research, we thoroughly investigated the Collaborative Indoor Positioning Systems (CIPSs) for humans reported in the literature through a systematic review to obtain a state-of-the-art. We identified the system's architecture, infrastructure, technologies, techniques, methods, and evaluation metrics implemented on CIPSs, and studied their combined use. Based on the findings of the systematic review, we discovered that there are no publicly available databases to experimentally test and validate ranging-based CIPSs considering heterogeneous mobile devices. Therefore, we collected experimental data considering real-world collaborative scenarios (i.e., office and lobby scenarios) and heterogeneous mobile devices to create an open access mobile device-based Bluetooth Low Energy (BLE) database, which is available together with its description and complementary material for reproducibility and extension. Moreover, we created BLE and IEEE 802.11 Wireless LAN (Wi-Fi) radio maps to estimate devices' position in the non-collaborative phase of CIPSs. Next, we devised a CIPS, consisting of three sequential phases. The calibration phase, which is used to register and calibrate heterogeneous mobiles devices that interact in the CIPS; the non-collaborative phase, where each device independently estimates its initial position based on a IPS, and the collaborative phase, which collaboratively enhance the estimated position of the target device/user. Traditional non-collaborative IPSs based on lateration and fingerprinting are part of the non-collaborative phase of our CIPSs and are used as benchmarks for evaluating them. Similarly, a lateration method, based on collaborative devices acting as anchors, and a distance estimation model are part of the collaborative phase of our

CIPSs. Given the importance of the traditional methods to estimate distance (i.e., based on Logarithmic Distance Path Loss (LDPL)) and position (i.e., RSSI-lateration and fingerprinting–k-Nearest Neighbors (k-NN)) as benchmarks and as part of our CIPS phases, we experimentally evaluated them considering mobile devices. As a result, we identified their limitations and challenges, and taking them into account, we proposed two non-collaborative solutions to improve the distance and positioning accuracy of the LDPL model and lateration methods, respectively. The first is a system that relates distance and RSSI values based on a fuzzy logic system to improve the distance estimation accuracy. The second is a lateration method based on an effective selection of available anchors to enhance positioning accuracy. Although they improve the distance and positioning accuracy, they are impractical in scenarios with heterogeneous devices and are not scalable. Considering all the takeaway points from the systematic review and the experiments carried out, we proposed a CIPS baseline scheme for developing CIPSs which allows us to enhance the positioning accuracy of traditional IPSs based on RSSI measurements (i.e., lateration and fingerprinting). Based on the CIPS scheme, we developed and experimentally evaluated two variants of a mobile device-based CIPS based on MLP ANNs model for improving positioning accuracy of lateration and fingerprinting–k-NN methods, respectively. The reason for implementing a MLP ANNs model instead of LDPL model in both variants is due to the complexity of the indoor environments and heterogeneity of mobile devices used in CIPS, also the well-known capacity of neural networks to learn and approximate patterns/functions based on the mapped inputs. The first variant is solely based on BLE technology and lateration and was tested in an office scenario with rich Non-line-of-sight (NLOS) conditions and a poor distribution and number of anchors. The second variant is a hybrid version, which can be used with BLE or Wi-Fi technologies together with fingerprinting–k-NN, and was tested in two real-world scenarios with diverse NLOS conditions. The implementation of the MLP ANNs model allows CIPSs to work in different scenarios, with different technologies, and outperform the aforementioned traditional IPS under specific conditions.

In the following sections, we address the research questions formulated at the beginning of this dissertation (see Section 1.2) together with the main conclusions. Moreover, we present the limitations of our proposed mobile device-based CIPS using MLP ANNs, propose some future research avenues to enhance the performance of CIPSs, and list the international journals, conferences, and repositories where our contributions and results were published.

6.1 Answers to research questions

RQ1: What are the infrastructures, architectures, technologies, techniques, methods, and evaluation aspects used in/for CIPSs, and what are the current trends and the main gaps in CIPS?

To answer this research question and provide an overall review of CIPSs, we performed a systematic review on CIPSs covering 99 significant papers from 2006 to 2022. The analysis carried out indicated increasing interest in the study of collaborative positioning among scientists and that decentralized architectures and infrastructure-less systems are becoming more popular. To analyze the technologies, techniques, and methods, we divided the CIPSs into non-collaborative and collaborative parts. Regarding the non-collaborative part, the findings revealed a broad variety of technologies, methodologies, and methods, making it challenging to identify a predominant combination. The popular coupled technology and technique, used in the non-collaborative part, are: Wi-Fi/RSSI, Wi-Fi/fingerprinting and Inertial Measurement Unit (IMU)/Dead Reckoning (DR). In the collaborative part, researchers prefer RSSI based on Wi-Fi and Bluetooth technologies. This is because these technologies are widely available, completely infrastructure-less, energy efficient, and inexpensive. With respect to methods, due to each of them having different goals, none of them stands out. Some CIPSs are based on a non-collaborative phase, which estimates the user's position non-collaboratively, and subsequently try to improve this estimate using a collaborative approach. Other CIPS are completely collaborative: they only use the non-collaborative part to collect the data, which is then processed by the collaborative method. Simulations are used as the main evaluation procedure. The predominant evaluation metrics in CIPSs in relevant order are position accuracy, computational complexity, computational complexity + robustness, position precision, robustness, and energy. The main gaps identified are that the majority of evaluation of CIPSs is based on simulations and only a few of them consider realistic collaborative scenarios including diverse devices. Therefore, providing databases containing positioning data involving various users/mobile devices and real-world scenarios could be beneficial for the reproducibility, repeatability, and evaluation of CIPSs and motivate the development of more CIPS. Also, only a scarce number of CIPSs take into account the users' privacy and security, the inclusion of heterogeneous devices, and none considered the inclusion of heterogeneous positioning systems in collaborative devices (devices using diverse technologies, techniques, and methods for positioning in the non-collaborative phase). Further information related to **RQ1** is provided in Chapter 2 and in [3].

RQ2: How can the ranging-based collaborative indoor positioning systems be experimentally tested and validated considering heterogeneous mobile devices?

Based on the information provided by the systematic review on CIPSs presented in Chapter 2, we identify that approximately half of the examined articles use simulations to evaluate CIPSs mainly to avoid the expensive hardware deployment and intensive physical labor needed in the experimental evaluation. Although advanced simulation algorithms can reproduce conditions similar to those present in real scenarios, experimental tests to validate the performance of CIPS under real scenarios are still needed.

To the best of our knowledge, there are no publicly available databases, before we published ours in [21, 23], that allow us to experimentally test and validate ranging-based CIPSs considering the transmission and reception from multiple mobile devices. Specifically, we created a mobile device-based BLE database for testing and validating ranging CIPSs, considering bidirectional and simultaneous transmission/reception between devices. The data was collected experimentally in two real indoor scenarios (office and lobby scenarios), considering different mobile devices diversely distributed (configurations) in the scenarios. We provide the description, usage examples, and supplementary material to guarantee the usability, reproducibility, and extension of the mobile device-based BLE database. In addition to this database, we created three radio maps (Wi-Fi and BLE fingerprint and BLE lateration), which are used to (non-collaboratively) estimate the position of a collaborative mobile device. The information contained in the mobile device-based BLE database together with the BLE and Wi-Fi radio maps of the office and lobby scenarios were used to evaluate and analyze our own approaches proposed in Chapter 4 and Chapter 5. Detailed information about the database and radio maps is provided in Chapter 3 and [21, 23].

RQ3: What are the limitations and challenges of the traditional methods to esti-

mate distance (i.e., based on LDPL model and fuzzy logic) and position (lateration and fingerprinting–k-NN) based on BLE/Wi-Fi-RSSI and how can the positioning accuracy and robustness of LDPL model and lateration be improved?

Our two variants of a mobile device-based CIPSs proposed in Chapter 5 aim to improve traditional IPSs, which we experimentally validated by integrating a lateration and fingerprinting positioning system in the non-collaborative phase and the lateration and a distance estimation model in the collaborative phase of our CIPSs. To understand any possible improvement of our collaborative positioning system, it is important to first evaluate the non-collaborative part and identify its limitations and challenges. To this end, we experimentally evaluated the traditional methods to estimate distance (i.e., based on LDPL model and fuzzy logic) and position (RSSI-lateration and fingerprinting–*k*-NN) based on BLE/Wi-Fi-RSSI and mobile devices to identify their limitations and challenges. Moreover, we proposed an innovative lateration method to enhance the accuracy and reliability of position estimation and an alternative system to the LDPL model that improves distance estimation accuracy. The first, lateration method, is based on an effective and combinatorial BLE anchors selection, and the second, alternative system, on a fuzzy classifier that replaces the LDPL model to estimate the distance.

Regarding the distance estimation based on the LDPL model, we found that the behavior of BLE signal propagation indoors and under Line-of-sight (LOS) does not follow the expected logarithmic attenuation. Instead, it varies depending on the transmitter device and indoor environment used. The main causes could be the diverse and unstable power transmission of each device and signal fluctuations generated by the environment's geometry. Therefore, it is impractical to provide a unique set of LDPL model parameters that work for various devices and scenarios. We have shown that it is possible to outperform the LDPL model distance accuracy and robustness with a system based on fuzzy logic. However, a limitation of our fuzzy logic approach is that it cannot offer robustness against power transmission variations, due to how we set the membership functions (i.e., based on the first, second, and third quartiles of the RSSI values measured at each reference point). In other words, if the power transmission of each device is different from the one used in training, the membership functions will be shifted and provide inaccurate estimations.

Regarding the lateration method based on RSSI, its main sources of positioning inaccuracy depend on two factors: first, the inadequate distribution (density and geometric position) of chosen BLE anchors; and second, large errors in the distance estimation between an unknown target and reference BLE anchors. To address this and improve the reliability and positioning accuracy of lateration approaches, we proposed a method capable of exploiting the availability and geometric distribution of BLE anchors, and effectively selecting a subset of them. Although our method improves the positioning accuracy and does not use sine and cosine computations to select the adequate anchors as in Geometric Dilution of Precision (GDOP), one of its limitations is the computational load to evaluate all possible combinations of deployed anchors. Therefore, to guarantee computational feasibility, we limited the maximum total number of available BLE anchors to 9 ($K = 9$ in Eq. 4.6).

With respect to fingerprinting evaluation, the analysis of the effect of the numbers of BLE anchors used to build the radio map, and the values of k nearest neighbors of k-NN algorithm on positioning accuracy demonstrated the following: first, a low number of BLE anchors (below ten BLE anchors) decrement the positioning accuracy considerably in fingerprinting. Second, the values of k as the number of BLE anchors increases are less relevant to the positioning accuracy. In general, the design of alternative methods that help to improve the positioning accuracy of lateration and fingerprinting when there are few anchors available in the environment is an open issue. Additionally, estimating the distance between devices in indoor scenarios, considering different scenarios and heterogeneous devices is an open challenge too. Detailed information about the limitations and challenges, as well as the implementation and evaluation of the approaches used are provided in Chapter 4 and in [21, 4, 6].

RQ4: *How can the positioning accuracy of traditional IPSs based on RSSI measurements (i.e., lateration and fingerprinting) be enhanced by the collaboration of surrounding devices/users?*

In order to enhance the positioning accuracy of traditional IPSs based on RSSI measurements (i.e., lateration and fingerprinting), we proposed a versatile and straightforward CIPS baseline scheme designed for developing CIPSs. CIPSs are systems that determine the position as a result of the indirect/direct interoperability between nearby actors/users or several IPSs. The scheme considered the most important aspects presented in our CIPS systematic review, namely the concept of compatibility among CIPS, system modularity, architecture (decentralized), and infrastructure (able to work as infrastructure-based and infrastructure-free). The baseline scheme divides the CIPS into 3 phases. In the first phase (calibration), the heterogenous devices are registered and a calibration process is carried out to allow the system to use them. In the non-collaborative phase, each device of the system estimates its initial position through traditional non-collaborative IPSs. In the collaborative phase, the positioning accuracy of the target device/user, estimated in the previous phase, is improved based on the exchange of information gathered in the previous phase between collaborative devices and the estimation of the relative distance between them.

Specifically, we developed and experimentally evaluated two variants of a mobile device-based CIPS based on MLP ANNs model, considering different base technologies (i.e., Wi-Fi and BLE), methods (i.e., lateration and fingerprinting–k-NN), and the two real-world scenarios (i.e. office and lobby scenario) and data described in Chapter 3. In our CIPS, in addition to using the surrounding mobile device to extend the positioning network, we proposed a novel model to estimate the relative distance between collaborative mobile devices based on the MLP ANNs model instead of the LDPL model. As mentioned above, LDPL models are not practical for estimating the distance of heterogeneous mobile devices and cannot be used under diverse scenarios due to the diverse and unstable power transmission of each device and signal fluctuations generated by the environment's geometry. Our proposed neural network model improved the distance estimation by considering the relation between distance and RSSI patterns, the pairwise device positions, the identification of devices (transmitter and receiver), and the variation of RSSI measurements due to the devices' hardware heterogeneity.

The first variant of mobile device-based CIPS proposed to enhance the traditional lateration-based IPSs faces three issues that decrement the positioning accuracy of lateration-based IPSs. The first is the NLOS conditions and deficient anchors deployment. Second, inefficient modeling of the signal propagation. Third, the effect of device heterogeneity on positioning accuracy. The results of evaluating our CIPS demonstrated the feasibility and advantages of our approach to outperform the positioning accuracy of the traditional lateration-based IPS under the aforementioned challenging conditions. Moreover, considering the distances among collaborating devices in each configuration and the relative difference of the "Root Mean

Square Error (RMSE)", "mean" and "75th percentile" metric, our proposed CIPS demonstrated that it significantly outperforms the lateration baseline in configuration 1 (short distances $\leq 4\,\mathrm{m}$), moderately outperforms the lateration baseline in configuration 4 ($4\,\mathrm{m} <$ medium distances $\leq 8\,\mathrm{m}$), and a slightly less in configuration 5 (large distances $> 8\,\mathrm{m}$). Regarding the second variant of CIPS proposed to enhance the traditional fingerprinting-based IPSs, although we designed a similar system (same CIPS baseline scheme), the new proposed MLP ANNs model presents a different architecture, which enables to the collaborative system to work under diverse scenarios (i.e., both office and lobby scenarios) and technologies (i.e., BLE and Wi-Fi). The new architecture is designed to process the input data provided by fingerprinting–k-NN instead of lateration methods of the non-collaborative phase. The results demonstrated that: for short distances among collaborating devices, our proposed approach outperforms the traditional IPSs based on BLE–fingerprinting and Wi-Fi–fingerprinting with a maximum error reduction of 23.41% and 19.49% for the "75th percentile" and "90th percentile" metric, respectively; for medium distances, our proposed approach outperforms the traditional IPSs based on BLE–fingerprinting in the first 60% and after the 90% of cases in the Empirical Cumulative Distribution Function (ECDF) and only partially (20% of cases in the ECDF) the traditional IPSs based on Wi-Fi–fingerprinting; for larger distances, our proposed approach performance is worse than the traditional IPSs based on fingerprinting, and in such cases, it is better to fall back on the non-collaborative estimation. Further details of the CIPSs proposed are provided in Chapter 5 and [22]. Additionally, we performed a literature-based comparison of our proposed CIPS variants with existing state-of-the-art (SOTA) CIPSs. The results showed that our proposed systems achieve comparable or better accuracy than the SOTA systems while using heterogeneous devices and NLOS conditions in the test scenarios. Also that their complexity is comparable with the SOTA systems evaluated.

Overall, the results demonstrated the usefulness of our CIPS baseline scheme to develop new CIPS considering different technologies (i.e., Wi-Fi and BLE) and methods (i.e., lateration and fingerprinting–k-NN) to improve the positioning accuracy of traditional IPSs, namely IPSs based on BLE–lateration, BLE–fingerprinting, and Wi-Fi–fingerprinting. Specifically, our first variant of mobile device-based CIPS using MLP ANNs proposed demonstrated that outperforms the positioning accuracy of the lateration baseline in all the configurations tested (i.e., where the collaborative devices have short, medium, and large distances between them), the second variant of mobile device-based CIPS using MLP ANNs proposed demonstrated that CIPS enhances the positioning accuracy of traditional IPSs based on fingerprinting under specific conditions (i.e., where the collaborative devices have short and medium distances between them). Moreover, the integration of MLP ANNs model in CIPSs allows us to use our approach under different scenarios and for different technologies, showing its generality, feasibility and usefulness.

6.2 Limitations

Although the two proposed variants of mobile device-based CIPS using MLP ANNs enhance the positioning accuracy of traditional IPSs based on RSSI under specific conditions, one of the main disadvantages is that its performance depends on the distance between collaborative mobile devices (mobile device density). Specifically, the positioning accuracy of our proposed CIPS decreases as the distance between collaborative mobile devices increases. In other words, the usefulness of our MLP ANNs model used to estimate distance is limited in scenarios where the distance between mobile devices is large. Therefore, addressing those cases remains an open issue. Nevertheless, for moderate or high density of mobile devices – and thus short and medium distances between mobile devices – as present in the real indoor scenarios, our proposal provides an improvement compared to IPSs.

The advantages of using the widely available embedded technologies in wearable/-mobile devices for positioning are well known. Our CIPS has been implemented using Wi-Fi and BLE technologies for both the non-collaborative and collaborative parts. Those technologies are straightforward to implement, able to exchange data, and widely available in real-world scenarios and devices. On the downside, they only provide meter-level positioning accuracy. Also, to provide a balance between positioning accuracy and computational cost, our CIPS uses a single technology instead of technologies/sensors fusion. For example, technologies/sensors fusion requires methods based on particle filters that increase the computational load as the particle size increase (bigger particle size provides the best positioning accuracy). Therefore, the main advantages of our CIPS in terms of easy implementation and low computational cost, are also some possible limitations with respect to a more accurate positioning.

Our CIPS is based on MLP ANN, which must be trained in order to estimate the position. The size of the training datasets impacts the accuracy of the estimation. Our datasets consider a maximum of 9 diverse mobile devices, 2 scenarios, and 7 different configurations in each scenario where the mobile devices are placed statically. Therefore, the cases in which the devices are continuously moving in the scenarios were not analyzed. Also, the online and continuous positioning estimation of the devices was not considered.

6.3 Future research avenues

This thesis covered several aspects of CIPS in order to enhance traditional IPSs. However, the study and implementation of CIPSs encompass many study areas, leaving room for improvement. Therefore, based on the limitations previously identified, we suggest the following future research avenues to extend/improve our proposed solutions:

A future research avenue to mitigate the impact of low device density on the positioning accuracy of CIPS could be to test diverse machine-learning methods to increase the accuracy of inter-device distance estimation. For example, methods based on convolutional neural networks, which consider as input screenshots (i.e., heatmap image) based on the scenario area, the estimated position (x,y coordinates) of the mobile devices, and the RSSI measured between devices.

In the medium-large term, new technologies (e.g., 6G, Ultra-wide band (UWB)) with better positioning features could be widely embedded in wearable/mobile devices and used in the collaboration between devices of the CIPSs. Nowadays, UWB technology, which provides centimeter-level positioning accuracy, has been included in several flagship wearable/mobile devices (e.g., Google Pixel 7, Samsung S22, iPhone 14, AirTags, MagSafe Charging Case for AirPods Pro, among others). Nevertheless, in public areas, UWB anchors are currently not yet deployed on large scale. Therefore, in addition to our previously proposed research avenue, we suggest two more research avenues to enhance the overall positioning accuracy of our CIPS based on the new technologies and technologies/sensors fusion. First, we could implement and study the use of UWB technology embedded in the devices (device-based UWB anchors) to increase the accuracy of the inter-device distance estimated in the collaborative phase. Also, to guarantee compatibility with the technologies deployed in the scenarios, we could use Wi-Fi and/or BLE in the non-collaborative phase. Second, to perform a deep study and evaluate technologies/sensors fusion methods to propose a solution that balances low computational cost and positioning accuracy.

In Chapter 3, we presented an open access mobile device-based BLE database for testing and validating ranging CIPSs. The database can be continuously extended considering other indoor scenarios, configurations, and mobile devices, and include diverse rotations or positions of devices on the body to enrich the database's diversity and allow the research community to train and test their CIPSs experimentally under diverse conditions. In addition, another future work could be the design of a multi-platform application that allows users to position themselves in real-time and collaboratively in the scenarios (i.e., based on scenarios' maps) and that can also be used for straightforward data collection.

6.4 Impact of publication and supporting material

The contributions and results presented in this thesis correspond to the outcomes of the scientific works conducted by the author at the Institute of New Imaging Technologies, University Jaume I (Castellón, Spain) and Electrical Engineering Unit, Tampere University (Tampere, Finland), between 2019 and 2022, which have been published in international journals [3, 21], and renowned international conferences [4, 6, 22]. The journal article [3] has been selected as an "Editor's Choice Article". The supporting materials, software and datasets, have been published in open access repositories [23, 188].

REFERENCES

[1] Anahid Basiri, Elena Simona Lohan, Terry Moore, Adam Winstanley, Pekka Peltola, Chris Hill, Pouria Amirian, and Pedro Figueiredo e Silva. "Indoor location based services challenges, requirements and usability of current solutions". In: *Computer Science Review* 24 (2017), pp. 1–12.

[2] *Indoor Location Based Services Market Research Report by Technology, Device, Industry, Application, and Region - Global Forecast to 2026 - Cumulative Impact of COVID-19*. https://www.researchandmarkets.com/reports/4896758/indoor-location-based-services-market-research. 2021.

[3] Pavel Pascacio, Sven Casteleyn, Joaquin Torres-Sospedra, Elena Simona Lohan, and Jari Nurmi. "Collaborative indoor positioning systems: A systematic review". In: *Sensors* 21.3 (2021), p. 1002.

[4] Pavel Pascacio, Sven Casteleyn, and Joaquín Torres-Sospedra. "Smartphone distance estimation based on rssi-fuzzy classification approach". In: *2021 International Conference on Localization and GNSS (ICL-GNSS)*. IEEE. 2021, pp. 1–6.

[5] Aleksandr Ometov, Viktoriia Shubina, Lucie Klus, Justyna Skibińska, Salwa Saafi, Pavel Pascacio, Laura Flueratoru, Darwin Quezada Gaibor, Nadezhda Chukhno, Olga Chukhno, et al. "A survey on wearable technology: History, state-of-the-art and current challenges". In: *Computer Networks* 193 (2021), p. 108074.

[6] Pavel Pascacio, Joaquín Torres-Sospedra, and Sven Casteleyn. "A Lateration Method based on Effective Combinatorial Beacon Selection for Bluetooth Low Energy Indoor Positioning". In: *2021 17th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob)*. IEEE. 2021, pp. 397–402.

[7] Gary Cullen, Kevin Curran, Jose Santos, Gearoid Maguire, and Denis Bourne. "CAPTURE—Cooperatively applied positioning techniques utilizing range extensions". In: *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2014, pp. 340–346.

[8] Gary Cullen, Kevin Curran, Jose Santos, Gearoid Maguire, and Denis Bourne. "To wireless fidelity and beyond—CAPTURE, extending indoor positioning systems". In: *2014 Ubiquitous Positioning Indoor Navigation and Location Based Service (UPINLBS)*. IEEE. 2015, pp. 248–254.

[9] Gary Cullen, Kevin Curran, Jose Santos, Gearoid Maguire, and Denis Bourne. "CAPTURE-Extending the scope of self-localization in Indoor Positioning Systems". In: *2015 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2015, pp. 1–10.

[10] C. Qiu and M.W. Mutka. "CRISP: cooperation among smartphones to improve indoor position information". In: *Wireless Networks* 24.3 (2018), pp. 867–884.

[11] Viet-Cuong Ta, Trung-Kien Dao, Dominique Vaufreydaz, and Eric Castelli. "Smartphone-based user positioning in a multiple-user context with Wi-Fi and Bluetooth". In: (2018), pp. 206–212.

[12] Ihsan A Lami, Halgurd S Maghdid, and Torben Kuseler. "SILS: A Smart Indoors Localisation Scheme Based on on-the-go Cooperative Smartphones Networks Using Onboard Bluetooth, WiFi and GNSS". In: *Proceedings of the 27th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2014)*. 2014, pp. 503–509.

[13] Rico Mendrzik and Gerhard Bauch. "Position-constrained stochastic inference for cooperative indoor localization". In: *IEEE Transactions on Signal and Information Processing over Networks* 5.3 (2019), pp. 454–468.

[14] Gabriel E Garcia, Henk Wymeersch, William Riblier, and Alexandre Cazalis. "Cooperative localization with 802.15. 4a CSS radios: Robustness to node failures". In: *2012 9th Workshop on Positioning, Navigation and Communication*. IEEE. 2012, pp. 7–12.

[15] Qian Zhao, Yang Liu, Huiqiang Wang, Hongwu Lv, Guangsheng Feng, and Mao Tang. "A cooperative indoor localization method based on spatial analysis". In: *Communications in Computer and Information Science* 901 (2018), pp. 628–637.

[16] Guofu Yong, Zhuoran Cai, and Hao Dong. "A high precision indoor cooperative localization scheme based on UWB signals". In: *International Conference on Wireless and Satellite Systems*. Springer. 2019, pp. 628–636.

[17] Si Wen Chen and Soon Yim Tan. "Cooperative non-line-of-sight localization technique for indoor wireless network". In: *2011 8th International Conference on Information, Communications & Signal Processing*. IEEE. 2011, pp. 1–5.

[18] Musa Furkan Keskin, Osman Erdem, and Sinan Gezici. "Cooperative Localization in Hybrid Infrared/Visible Light Networks: Theoretical Limits and Distributed Algorithms". In: *IEEE Transactions on Signal and Information Processing over Networks* 5.1 (2019), pp. 181–197.

[19] Henk Wymeersch, Jaime Lien, and Moe Z. Win. "Cooperative localization in wireless networks". In: *Proceedings of the IEEE* 97.2 (2009), pp. 427–450.

[20] Google. *Android Developers Reference*. https://developer.android.com/reference/android/bluetooth/le/ScanResult [Last visit: 30.11.2022].

[21] Pavel Pascacio, Joaquín Torres-Sospedra, Antonio R. Jiménez, and Sven Casteleyn. "Mobile device-based Bluetooth Low Energy Database for range estimation in indoor environments". In: *Scientific Data* 9.1 (2022), pp. 1–16.

[22] Pavel Pascacio, Joaquín Torres–Sospedra, Sven Casteleyn, and Elena Simona Lohan. "A Collaborative Approach Using Neural Networks for BLE-RSS Lateration-Based Indoor Positioning". In: *2022 International Joint Conference on Neural Networks (IJCNN)*. IEEE. 2022, pp. 01–09.

[23] Pavel Pascacio, Joaquín Torres-Sospedra, Antonio R. Jiménez, and Sven Casteleyn. *Supplementary Materials for 'Mobile device-based Bluetooth Low Energy Database for range estimation in collaborative positioning'*. https://doi.org/10.5281/zenodo.6463354. 2021.

[24] Wei Jiang, Yong Li, Chris Rizos, Baigen Cai, and Wei Shangguan. “Seamless Indoor-Outdoor Navigation based on GNSS, INS and Terrestrial Ranging Techniques”. In: *Journal of Navigation* 70.6 (2017), pp. 1183–1204.

[25] Shashi Shekhar and Hui Xiong. *Encyclopedia of GIS*. 2nd. Springer Publishing Company, Incorporated, 2008, p. 553. ISBN: 978-0-387-35973-1.

[26] Nelson Marques, Filipe Meneses, and Adriano Moreira. “Combining similarity functions and majority rules for multi-building, multi-floor, WiFi positioning”. In: *2012 International conference on indoor positioning and indoor navigation (IPIN)*. IEEE. 2012, pp. 1–9.

[27] Óscar Belmonte-Fernández, Adrian Puertas-Cabedo, Joaquín Torres-Sospedra, Raúl Montoliu-Colás, and Sergi Trilles-Oliver. “An indoor positioning system based on wearables for ambient-assisted living”. In: *Sensors* 17.1 (2016), p. 36.

[28] Dragan Ahmetovic, Masayuki Murata, Cole Gleason, Erin Brady, Hironobu Takagi, Kris Kitani, and Chieko Asakawa. “Achieving Practical and Accurate Indoor Navigation for People with Visual Impairments”. In: *Proceedings of the 14th Web for All Conference on The Future of Accessible Work*. 2017, pp. 1–10.

[29] A Karmacharya, GM Mendoza-Silva, and J Torres-Sospedra. “Sensor Fusion and Well Condition Triangle Approach forBLE-based Indoor Positioning”. In: *Proceedings of the Tenth International Conference on Localization and GNSS (ICL-GNSS-WIP 2020) Co-Located with the Tenth International Conference on Indoor Positioning and Indoor Navigation (ICL-GNSS 2020), Tampere, Finland*. 2020, pp. 2–4.

[30] Jun Qi and Guo-Ping Liu. “A robust high-accuracy ultrasound indoor positioning system based on a wireless sensor network”. In: *Sensors* 17.11 (2017), p. 2554.

[31] Yiwei Li, Zabih Ghassemlooy, Xuan Tang, Bangjiang Lin, and Yi Zhang. “A VLC smartphone camera based indoor positioning system”. In: *IEEE Photonics Technology Letters* 30.13 (2018), pp. 1171–1174.

[32] Daquan Feng, Chunqi Wang, Chunlong He, Yuan Zhuang, and Xiang-Gen Xia. “Kalman-filter-based integration of IMU and UWB for high-accuracy indoor positioning and navigation”. In: *IEEE Internet of Things Journal* 7.4 (2020), pp. 3133–3146.

[33] Seppo Horsmanheimo, Sergio Lembo, Lotta Tuomimaki, Sami Huilla, Petri Honkamaa, Matti Laukkanen, and Paul Kemppi. “Indoor positioning platform to support 5G location based services”. In: *2019 IEEE International Conference on Communications Workshops (ICC Workshops)*. IEEE. 2019, pp. 1–6.

[34] Marco Driusso, Chris Marshall, Mischa Sabathy, Fabian Knutti, Heinz Mathis, and Fulvio Babich. “Indoor positioning using LTE signals”. In: *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2016, pp. 1–8.

[35] Abdelmoula Bekkali, Horacio Sanson, and Mitsuji Matsumoto. “RFID indoor positioning based on probabilistic RFID map and Kalman filtering”. In: *Third IEEE International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob 2007)*. IEEE. 2007, pp. 21–21.

[36] Zhu Jianyong, Luo Haiyong, Chen Zili, and Li Zhaohui. “RSSI based Bluetooth low energy indoor positioning”. In: *2014 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2014, pp. 526–533.

[37] Enrique García, Pablo Poudereux, Álvaro Hernández, Jesús Ureña, and David Gualda. “A robust UWB indoor positioning system for highly complex environments”. In: *2015 IEEE International Conference on Industrial Technology (ICIT)*. IEEE. 2015, pp. 3386–3391.

[38] Paramvir Bahl and Venkata N. Padmanabhan. “RADAR: An in-building RF-based user location and tracking system”. In: *Proceedings IEEE INFOCOM 2000. Conference on computer communications. Nineteenth annual joint conference of the IEEE computer and communications societies (Cat. No. 00CH37064)*. Vol. 2. IEEE. 2000, pp. 775–784.

[39] Adriano Moreira and Filipe Meneses. “Where@ UM-Dependable organic radio maps”. In: *2015 international conference on indoor positioning and indoor navigation (IPIN)*. IEEE. 2015, pp. 1–9.

[40] Demetrios Zeinalipour-Yazti and Christos Laoudias. “The anatomy of the anyplace indoor navigation service”. In: *SIGSPATIAL Special* 9.2 (2017), pp. 3–10.

[41] Youngtae Noh, Hirozumi Yamaguchi, and Uichin Lee. “Infrastructure-Free Collaborative Indoor Positioning Scheme for Time-Critical Team Operations”. In: *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 48.3 (2018), pp. 418–432.

[42] Antoni Pérez-Navarro, Joaquín Torres-Sospedra, Raul Montoliu, Jordi Conesa, Rafael Berkvens, Giuseppe Caso, Constantinos Costa, Nicola Dorigatti, Noelia Hernández, Stefan Knauth, Elena Simona Lohan, Juraj Machaj, Adriano Moreira, and Pawel Wilk. “1 - Challenges of Fingerprinting in Indoor Positioning and Navigation”. In: *Geographical and Fingerprinting Data to Create Systems for Indoor Positioning and Indoor/Outdoor Navigation*. Intelligent Data-Centric Systems. Academic Press, 2019, pp. 1–20.

[43] Zakaria Kasmi, Abdelmoumen Norrdine, and Jörg Blankenbach. “Platform architecture for decentralized positioning systems”. In: *Sensors* 17.5 (2017), p. 957.

[44] Yuanyi Chen, Minyi Guo, Jiaxing Shen, and Jiannong Cao. “GraphLoc: A graph-based method for indoor subarea localization with zero-configuration”. In: *Personal and Ubiquitous Computing* 21.3 (2017), pp. 489–505.

[45] Laura A. Merry, Ramsey M. Faragher, and Steve Scheding. “Comparison of opportunistic signals for localisation”. In: *IFAC Proceedings Volumes* 43.16 (2010), pp. 109–114.

[46] Maarten Weyn, Martin Klepal, et al. “Adaptive motion model for a smartphone based opportunistic localization system”. In: *International Workshop on Mobile Entity Localization and Tracking in GPS-less Environments*. Springer. 2009, pp. 50–65.

[47] Michael Robinson and Robert Ghrist. “Topological localization via signals of opportunity”. In: *IEEE transactions on signal processing* 60.5 (2012), pp. 2362–2373.

[48] Germán Martín Mendoza-Silva, Joaquín Torres-Sospedra, and Joaquín Huerta. “A meta-review of indoor positioning systems”. In: *Sensors* 19.20 (2019), p. 4507.

[49] Wilson Sakpere, Michael Adeyeye-Oshin, and Nhlanhla BW Mlitwa. “A state-of-the-art survey of indoor positioning and navigation systems and technologies”. In: *South African Computer Journal* 29.3 (2017), pp. 145–197.

[50] Ahasanun Nessa, Bhagawat Adhikari, Fatima Hussain, and Xavier N Fernando. “A Survey of Machine Learning for Indoor Positioning”. In: *IEEE Access* 8 (2020), pp. 214945–214965.

[51] Hui Liu, Houshang Darabi, Pat Banerjee, and Jing Liu. “Survey of wireless indoor positioning techniques and systems”. In: *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)* 37.6 (2007), pp. 1067–1080.

[52] R. Mautz. “Indoor positioning technologies”. PhD thesis. ETH Zürich, 2012.

[53] Faheem Zafari, Athanasios Gkelias, and Kin K Leung. “A survey of indoor localization systems and technologies”. In: *IEEE Communications Surveys & Tutorials* 21.3 (2019), pp. 2568–2599.

[54] Yanying Gu, Anthony Lo, and Ignas Niemegeers. “A survey of indoor positioning systems for wireless personal networks”. In: *IEEE Communications surveys & tutorials* 11.1 (2009), pp. 13–32.

[55] Suining He and S-H Gary Chan. “Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons”. In: *IEEE Communications Surveys & Tutorials* 18.1 (2015), pp. 466–490.

[56] Ismail Guvenc and Chia-Chin Chong. “A survey on TOA based wireless localization and NLOS mitigation techniques”. In: *IEEE Communications Surveys & Tutorials* 11.3 (2009), pp. 107–124.

[57] Ali Yassin, Youssef Nasser, Mariette Awad, Ahmed Al-Dubai, Ran Liu, Chau Yuen, Ronald Raulefs, and Elias Aboutanios. “Recent advances in indoor localization: A survey on theoretical approaches and applications”. In: *IEEE Communications Surveys & Tutorials* 19.2 (2016), pp. 1327–1346.

[58] Cristiano Pendao and Adriano Moreira. “FastGraph enhanced: High accuracy automatic indoor navigation and mapping”. In: *IEEE Transactions on Mobile Computing* 20.3 (2019), pp. 1027–1045.

[59] Noelia Hernández, Manuel Ocaña, Jose M. Alonso, and Euntai Kim. “Continuous space estimation: Increasing WiFi-based indoor localization resolution without increasing the site-survey effort”. In: *Sensors* 17.1 (2017), p. 147.

[60] Yanzhen Ye and Bang Wang. “RMapCS: Radio map construction from crowdsourced samples for indoor localization”. In: *IEEE Access* 6 (2018), pp. 24224–24238.

[61] Giuseppe Caso, Luca De Nardis, Filip Lemic, Vlado Handziski, Adam Wolisz, and Maria-Gabriella Di Benedetto. “ViFi: Virtual Fingerprinting WiFi-Based Indoor Positioning via Multi-Wall Multi-Floor Propagation Model”. In: *IEEE Transactions on Mobile Computing* 19.6 (2020), pp. 1478–1491.

[62] Syed Khandker, Joaquín Torres-Sospedra, and Tapani Ristaniemi. “Improving RF fingerprinting methods by means of D2D communication protocol”. In: *Electronics* 8.1 (2019), p. 97.

[63] Yongtao Ma, Chenglong Tian, and Yue Jiang. “A multitag cooperative localization algorithm based on weighted multidimensional scaling for passive UHF RFID”. In: *IEEE Internet of Things Journal* 6.4 (2019), pp. 6548–6555.

[64] Sijia Yu, Xin Su, Jie Zeng, and Huanxi Cui. “Mobility assisted wireless sensor network cooperative localization via SOCP”. In: *Lecture Notes of the Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering, LNICST* 258 (2019), pp. 129–138.

[65] Thomas Gallagher, Elyse Wise, Binghao Li, Andrew G Dempster, Chris Rizos, and Euan Ramsey-Stewart. “Indoor positioning system based on sensor fusion for the blind and visually impaired”. In: *2012 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2012, pp. 1–9.

[66] Sebastian Hilsenbeck, Dmytro Bobkov, Georg Schroth, Robert Huitl, and Eckehard Steinbach. “Graph-Based Data Fusion of Pedometer and WiFi Measurements for Mobile Indoor Positioning”. In: *Proceedings of the 2014*

ACM International Joint Conference on Pervasive and Ubiquitous Computing. Association for Computing Machinery, 2014, pp. 147–158.

[67] Ubejd Shala and Angel Rodriguez. *Indoor positioning using sensor-fusion in android devices*. 2011.

[68] Manon Kok, Jeroen D Hol, and Thomas B Schön. "Indoor positioning using ultrawideband and inertial measurements". In: *IEEE Transactions on Vehicular Technology* 64.4 (2015), pp. 1293–1303.

[69] Reza Zekavat and R Michael Buehrer. *Handbook of position location: Theory, practice and advances*. Vol. 27. John Wiley & Sons, 2011.

[70] Keith YK Leung, Timothy D Barfoot, and Hugh HT Liu. "Distributed and decentralized cooperative simultaneous localization and mapping for dynamic and sparse robot networks". In: *2011 IEEE International Conference on Robotics and Automation*. IEEE. 2011, pp. 3841–3847.

[71] Alessandro Liberati, Douglas G Altman, Jennifer Tetzlaff, Cynthia Mulrow, Peter C Gøtzsche, John PA Ioannidis, Mike Clarke, Philip J Devereaux, Jos Kleijnen, and David Moher. "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration". In: *Journal of clinical epidemiology* 62.10 (2009), e1–e34.

[72] Li-wei Chan, Ji-rung Chiang, Yi-chao Chen, Chia-nan Ke, Jane Hsu, and Hao-hua Chu. "Collaborative localization: Enhancing WiFi-based position estimation with neighborhood links in clusters". In: *International Conference on Pervasive Computing*. Springer. 2006, pp. 50–66.

[73] Cheolsu Son, Namhyun Yoo, and Wonjung Kim. "Positioning system using dynamic location-convergence adjustment factor for wireless LAN infrastructures". In: *The Sixth IEEE International Conference on Computer and Information Technology*. IEEE Computer Society. 2006, pp. 233–233.

[74] Francescantonio Della Rosa, Satya Ardhy Wardana, Carlos Leonel Flores Mayorga, Gianluca Simone, Marie Claire Naima Raynal, Joao Figueiras, and Simone Frattasi. "Experimental activity on cooperative mobile positioning in indoor environments". In: *2007 IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks*. IEEE. 2007, pp. 1–6.

[75] Nayef A. Alsindi, Kaveh Pahlavan, and Bardia Alavi. “An error propagation aware algorithm for precise cooperative indoor localization”. In: *MILCOM 2006-2006 IEEE Military Communications conference* (2006), pp. 1–7.

[76] Jianfeng Chen and Xiaojun Ma. “Neighbor-assisted location calibration mechanism in wireless network”. In: *GLOBECOM 2009-2009 IEEE Global Telecommunications Conference*. IEEE. 2009, pp. 1–6.

[77] Francescantonio Della Rosa, Tommi Paakki, Helena Leppäkoski, and Jari Nurmi. “A cooperative framework for path loss calibration and indoor mobile positioning”. In: *2010 7th Workshop on Positioning, Navigation and Communication*. IEEE. 2010, pp. 86–92.

[78] Xinrong Li. “Collaborative multi-sensor tracking in mobile wireless sensor networks”. In: *International Journal of Sensor Networks* 8.3-4 (2010), pp. 233–246.

[79] Senka Hadzic and Jonathan Rodriguez. “Utility based node selection scheme for cooperative localization”. In: *2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2011, pp. 1–6.

[80] Bjorn Bittins and Jurgen Sieck. “Multisensor and collaborative localization for diverse environments”. In: *Proceedings - UKSim 5th European Modelling Symposium on Computer Modelling and Simulation, EMS 2011* (2011), pp. 406–411.

[81] Kamil Kloch, Gerald Pirkl, Paul Lukowicz, and Carl Fischer. “Emergent behaviour in collaborative indoor localisation: An example of self-organisation in ubiquitous sensing systems”. In: *International Conference on Architecture of Computing Systems*. Springer. 2011, pp. 207–218.

[82] R. Raulefs, S. Zhang, C. Mensing, C. Ghali, and J. Hachem. “Dynamic cooperative positioning”. In: *17th European Wireless Conference 2011, EW 2011* (2011), pp. 639–643.

[83] Gianni Giorgetti, Richard Farley, Kiran Chikkappa, Judy Ellis, and Telis Kaleas. “Cortina: Collaborative indoor positioning using low-power sensor networks”. In: *2011 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2011, pp. 1–10.

[84] Apostolia Papapostolou, Wendong Xiao, and Hakima Chaouchi. “Cooperative fingerprint-based indoor localization using Self-Organizing Maps”. In: *2011 7th International Wireless Communications and Mobile Computing Conference*. IEEE. 2011, pp. 1814–1819.

[85] Samuel Van de Velde, Henk Wymeersch, Paul Meissner, Klaus Witrisal, and Heidi Steendam. “Cooperative multipath-aided indoor localization”. In: *2012 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE. 2012, pp. 3107–3111.

[86] Sungnam Lee, Hyojeong Shin, and Hojung Cha. “A pedestrian tracking system using group mobility information”. In: *MILCOM 2012-2012 IEEE Military Communications Conference*. IEEE. 2012, pp. 1–6.

[87] Junghyun Jun, Yu Gu, Long Cheng, Banghui Lu, Jun Sun, Ting Zhu, and Jianwei Niu. “Social-Loc: Improving indoor localization with social sensing”. In: *Proceedings of the 11th ACM Conference on Embedded Networked Sensor Systems*. 2013, pp. 1–14.

[88] M. Froehle, E. Leitinger, P. Meissner, and K. Witrisal. “Cooperative multipath-assisted indoor navigation and tracking (Co-MINT) using UWB signals”. In: *2013 IEEE International Conference on Communications Workshops, ICC 2013* (2013), pp. 16–21.

[89] John-Olof Nilsson, Dave Zachariah, Isaac Skog, and Peter Händel. “Cooperative localization by dual foot-mounted inertial sensors and inter-agent ranging”. In: *EURASIP Journal on Advances in Signal Processing* 2013.1 (2013), pp. 1–17.

[90] Yi-Ting Li, Guaning Chen, and Min-Te Sun. “An indoor collaborative pedestrian dead reckoning system”. In: (2013), pp. 923–930.

[91] Hao Jing, James Pinchin, Chris Hill, and Terry Moore. “Wi-Fi indoor localisation based on collaborative ranging between mobile users”. In: *Proceedings of the 26th International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2013)*. 2013, pp. 1317–1324.

[92] Omotayo G. Adewumi, Tranos Zuva, and Seleman Ngwira. “Simulation and calibration of rssi based distance estimation for localization in WSN”. In: *Proceedings of the IASTED International Conference on Modelling and Simulation, AfricaMS 2014* (2014), pp. 124–131.

[93] Jack Brassil. “Improving indoor positioning accuracy with dense, cooperating beacons”. In: *Procedia Computer Science* 40 (2014), pp. 1–8.

[94] Gemma Morral and Ndeye Amy Dieng. “Cooperative RSSI-based indoor localization: B-MLE and distributed stochastic approximation”. In: *2014 IEEE 80th Vehicular Technology Conference (VTC2014-Fall)*. IEEE. 2014, pp. 1–5.

[95] Fredrik Olsson, Jouni Rantakokko, and Jonas Nygårds. “Cooperative localization using a foot-mounted inertial navigation system and ultrawideband ranging”. In: *IPIN 2014 - 2014 International Conference on Indoor Positioning and Indoor Navigation* (2014), pp. 122–131.

[96] Zhice Yang, Xiaojun Feng, and Qian Zhang. “Adometer: Push the limit of pedestrian indoor localization through cooperation”. In: *IEEE Transactions on Mobile Computing* 13.11 (2014), pp. 2473–2483.

[97] D. Taniuchi, X. Liu, D. Nakai, and T. Maekawa. “Spring Model Based Collaborative Indoor Position Estimation with Neighbor Mobile Devices”. In: *IEEE Journal on Selected Topics in Signal Processing* 9.2 (2015), pp. 268–277.

[98] Shenghong Li, Mark Hedley, and Iain B Collings. “New efficient indoor cooperative localization algorithm with empirical ranging error model”. In: *IEEE Journal on Selected Areas in Communications* 33.7 (2015), pp. 1407–1417.

[99] Xuyu Wang, Hui Zhou, Shiwen Mao, Santosh Pandey, Prathima Agrawal, and David M. Bevly. “Mobility improves LMI-based cooperative indoor localization”. In: *2015 IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE. 2015, pp. 2215–2220.

[100] Haofan Cai, Guang Wu, Yifan Chen, and Linshan Jiang. “Indoor collaborative localization method based on ultra-wideband ranging”. In: *2015 9th European Conference on Antennas and Propagation (EuCAP)*. IEEE. 2015, pp. 1–2.

[101] Reza Monir Vaghefi, SaiDhiraj Amuru, and R Michael Buehrer. “Improving mobile node tracking performance in NLOS environments using cooperation”. In: (2015), pp. 6595–6600.

[102] Kevin McDermott, Reza Monir Vaghefi, and R Michael Buehrer. "Cooperative UTDOA positioning in LTE cellular systems". In: (2015), pp. 1–6.

[103] Wendong Xiao, Apostolia Papapostolou, Hakima Chaouchi, and Ming Wei. "Self-organizing map for fingerprinting-based cooperative localization in dynamic indoor environments". In: *Unmanned Systems* 3.03 (2015), pp. 171–183.

[104] Marcin Kolakowski and Vitomir Djaja-Josko. "TDOA-TWR based positioning algorithm for UWB localization system". In: *2016 21st International Conference on Microwave, Radar and Wireless Communications (MIKON)*. IEEE. 2016, pp. 1–4.

[105] L. Chen, K. Yang, and X. Wang. "Robust Cooperative Wi-Fi Fingerprint-Based Indoor Localization". In: *IEEE Internet of Things Journal* 3.6 (2016), pp. 1406–1417.

[106] Fernando Seco, Antonio R Jiménez, and Xufei Zheng. "RFID-based centralized cooperative localization in indoor environments". In: (2016), pp. 1–7.

[107] Jun-Wei Qiu and Yu-Chee Tseng. "M2M encountering: Collaborative localization via instant inter-particle filter data fusion". In: *IEEE Sensors Journal* 16.14 (2016), pp. 5715–5724.

[108] Qiyue Li, Wei Li, Wei Sun, Jie Li, and Zhi Liu. "Fingerprint and Assistant Nodes Based Wi-Fi Localization in Complex Indoor Environment". In: *IEEE Access* 4 (2016), pp. 2993–3004.

[109] Hao Jing, James Pinchin, Chris Hill, and Terry Moore. "An adaptive weighting based on modified DOP for collaborative indoor positioning". In: *The Journal of Navigation* 69.2 (2016), pp. 225–245.

[110] Chen Ze, MU Hua, Chen Chang-hao, and Wu Mei-ping. "Implement of cooperative navigation in pedestrian navigation based on distance restraint". In: *CGNCC 2016 - 2016 IEEE Chinese Guidance, Navigation and Control Conference* (2017), pp. 2123–2127.

[111] Reza Monir Vaghefi and R Michael Buehrer. "Cooperative Source Node Tracking in Non-Line-of-Sight Environments". In: *IEEE Transactions on Mobile Computing* 16.5 (2017), pp. 1287–1299.

[112] M. Karlsson and F. Karlsson. “Cooperative indoor positioning by exchange of bluetooth signals and state estimates between users”. In: *2016 European Control Conference, ECC 2016* (2017), pp. 1440–1444.

[113] C.C. Chang, G.W. Lee, and T.Y. Lee. “Cooperative indoor localization with ranging and orientation data”. In: *Chung Cheng Ling Hsueh Pao/Journal of Chung Cheng Institute of Technology* 46.2 (2017), pp. 43–50.

[114] Aiden Morrison, Nadezda Sokolova, Trym V. Haavardsholm, Ove K. Hagen, Thomas O. Opsahl, Kjetil B. Anonsen, and Kapteinleytnant Erik H. Eriksen. “Collaborative indoor navigation for emergency services personnel”. In: *2017 IEEE Aerospace Conference*. IEEE. 2017, pp. 1–10.

[115] Po-Hsuan Tseng and Ke-Ting Lee. “A Femto-Aided Location Tracking Algorithm in LTE-A Heterogeneous Networks”. In: *IEEE Transactions on Vehicular Technology* 66.1 (2017), pp. 748–762.

[116] Yu Liu, TAIBAO Jiang, Yongle Lu, Xin Zhang, and Yunmei Li. “Indoor collaborative localization using multiple micro-electro-mechanical system sensor nodes”. In: *ICIC Express Lett. Part B Appl* 8 (2017), pp. 101–108.

[117] Jianan Zhu and Solmaz S Kia. “A loosely coupled cooperative localization augmentation to improve human geolocation in indoor environments”. In: *2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2018, pp. 206–212.

[118] Fernando Seco and Antonio R Jiménez. “Smartphone-based cooperative indoor localization with RFID technology”. In: *Sensors* 18.1 (2018), p. 266.

[119] Enwen Hu, Zhongliang Deng, Mudan Hu, Lu Yin, and Wen Liu. “Cooperative indoor positioning with factor graph based on FIM for wireless sensor network”. In: *Future Generation Computer Systems* 89 (2018), pp. 126–136.

[120] Zhenyu Liu, Wenhan Dai, and Moe Z. Win. “Mercury: An Infrastructure-Free System for Network Localization and Navigation”. In: *IEEE Transactions on Mobile Computing* 17.5 (2018), pp. 1119–1133.

[121] Rico Mendrzik and Gerhard Bauch. “Constrained stochastic inference for cooperative indoor localization”. In: *2017 IEEE Global Communications Conference, GLOBECOM 2017 - Proceedings* 2018-January (2017), pp. 1–6.

[122] Hailiang Xiong, Meixuan Peng, Shu Gong, and Zhengfeng Du. “A Novel Hybrid RSS and TOA Positioning Algorithm for Multi-Objective Cooperative Wireless Sensor Networks”. In: *IEEE Sensors Journal* 18.22 (2018), pp. 9343–9351.

[123] Xiaolong Geng, Mu Zhou, Yacong Wei, and Yunxia Tang. “Indoor WLAN collaborative localization algorithm based on geometric figure overlap”. In: (2016), pp. 515–524.

[124] Fang Yang, Junnan Gao, and Yuanpeng Liu. “Indoor visible light positioning system based on cooperative localization”. In: *Optical Engineering* 58.1 (2019).

[125] Xiaofeng Lu, Kun Yang, Jiayu Liu, Changlin Yang, Zibo Zhang, and Hailin Zhang. “Indoor Collaborative Positioning With Adaptive Particle-Pair Filtering Based on Dynamic User Pairing”. In: *IEEE Access* 7 (2019), pp. 5795–5807.

[126] Leïla Gazzah and Leïla Najjar. “Enhanced cooperative group localization with identification of LOS/NLOS BSs in 5G dense networks”. In: *Ad Hoc Networks* 89 (2019), pp. 88–96.

[127] Tiantian Zhao, Kun Zhao, Chao Yu, Danan Dong, Zhengqi Zheng, and Yu Zhang. “Application of Differential Time Synchronization in Indoor Positioning”. In: *2019 11th International Conference on Wireless Communications and Signal Processing (WCSP)*. IEEE. 2019, pp. 1–6.

[128] Tianyu Wang, Hanying Zhao, and Yuan Shen. “High-accuracy localization using single-anchor ultra-wide bandwidth systems”. In: *2019 IEEE/CIC International Conference on Communications in China (ICCC)*. IEEE. 2019, pp. 59–63.

[129] Jelena Gabela, Guenther Retscher, Salil Goel, Harris Perakis, Andrea Masiero, Charles Toth, Vassilis Gikas, Allison Kealy, Zoltán Koppányi, Wioleta Błaszczak-Bąk, et al. “Experimental evaluation of a UWB-based cooperative positioning system for pedestrians in GNSS-denied environment”. In: *Sensors* 19.23 (2019), p. 5274.

[130] Aiden Morrison, Laura Ruotsalainen, Maija Mäkelä, Jesperi Rantanen, and Nadeza Sokolova. “Combining visual, pedestrian, and collaborative navigation techniques for team based infrastructure free indoor navigation”. In: *Proceedings of the 32nd International Technical Meeting of the Satellite Division of The Institute of Navigation (ION GNSS+ 2019)*. 2019, pp. 2692–2701.

[131] Chun Wang, Juan Luo, and Qian He. “A Cooperative Indoor Localization Enhancement Framework on Edge Computing Platforms for Safety-Critical Applications”. In: *2019 15th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN)*. IEEE. 2019, pp. 372–377.

[132] Yik Him Ho and Henry CB Chan. “Decentralized adaptive indoor positioning protocol using Bluetooth Low Energy”. In: *Computer Communications* 159 (2020), pp. 231–244.

[133] Jiwon Jung, Yunyoung Choi, and Younggoo Kwon. “Location-Aware Point-to-Point RPL in Indoor IR-UWB Networks”. In: *Electronics* 9.5 (2020), p. 861.

[134] Xianshan Li, Yurun Shao, and Fengda Zhao. “An Indoor Positioning Approach Using Smartphone Based on PDR and EKF”. In: *2020 15th IEEE Conference on Industrial Electronics and Applications (ICIEA)*. IEEE. 2020, pp. 182–187.

[135] Ran Liu, Chau Yuen, Tri-Nhut Do, Meng Zhang, Yong Liang Guan, and U-Xuan Tan. “Cooperative positioning for emergency responders using self IMU and peer-to-peer radios measurements”. In: *Information Fusion* 56 (2020), pp. 93–102.

[136] Mostafa Sakr, Andrea Masiero, and Naser El-Sheimy. “LocSpeck: A Collaborative and Distributed Positioning System for Asymmetric Nodes Based on UWB Ad-Hoc Network and Wi-Fi Fingerprinting”. In: *Sensors* 20.1 (2020), p. 78.

[137] Mohamed Shalaby, Mona Shokair, and Nagy Wadie Messiha. “RSS Cooperative Localization in WSNs Operating in the Millimeter Bands”. In: *Wireless Personal Communications* 115.3 (2020), pp. 2327–2334.

[138] Viet-Cuong Ta, Trung-Kien Dao, Dominique Vaufreydaz, and Eric Castelli. “Collaborative Smartphone-Based User Positioning in a Multiple-User Context Using Wireless Technologies”. In: *Sensors* 20.2 (2020), p. 405.

[139] Josef Kulmer, Erik Leitinger, Paul Meissner, and Klaus Witrisal. "Cooperative multipath-assisted navigation and tracking: A low-complexity approach". In: *Future Access Enablers of Ubiquitous and Intelligent Infrastructures*. Springer. 2015, pp. 159–165.

[140] Cesare Alippi and Giovanni Vanini. "A RSSI-based and calibrated centralized localization technique for wireless sensor networks". In: *Fourth Annual IEEE International Conference on Pervasive Computing and Communications Workshops (PERCOMW'06)*. 2006, 5–pp.

[141] Huanhuan Wang, Jianchen Wan, and Ruyou Liu. "A novel ranging method based on RSSI". In: *Energy Procedia* 12 (2011), pp. 230–235.

[142] Gaddi Blumrosen, Bracha Hod, Tal Anker, Danny Dolev, and Boris Rubinsky. "Enhanced calibration technique for RSSI-based ranging in body area networks". In: *Ad hoc networks* 11.1 (2013), pp. 555–569.

[143] Po-Chou Liang and Paul Krause. "Smartphone-based real-time indoor location tracking with 1-m precision". In: *IEEE journal of biomedical and health informatics* 20.3 (2015), pp. 756–762.

[144] Alberto Belmonte-Hernández, Gustavo Hernandez-Penaloza, Federico Alvarez, and Giuseppe Conti. "Adaptive fingerprinting in multi-sensor fusion for accurate indoor tracking". In: *IEEE Sensors Journal* 17.15 (2017), pp. 4983–4998.

[145] Nathan Dwek, Merwan Birem, Kurt Geebelen, Erik Hostens, Anurodh Mishra, Jan Steckel, and Risang Yudanto. "Improving the accuracy and robustness of ultra-wideband localization through sensor fusion and outlier detection". In: *IEEE Robotics and Automation Letters* 5.1 (2019), pp. 32–39.

[146] Yaping Zhu, Feng Yan, Shengjie Zhao, Fei Shen, Song Xing, and Lianfeng Shen. "Incentive mechanism for cooperative localization in wireless networks". In: *IEEE Transactions on Vehicular Technology* 69.12 (2020), pp. 15920–15932.

[147] Feng Yin, Zhidi Lin, Qinglei Kong, Yue Xu, Deshi Li, Sergios Theodoridis, and Shuguang Robert Cui. "FedLoc: Federated learning framework for data-driven cooperative localization and location data processing". In: *IEEE Open Journal of Signal Processing* 1 (2020), pp. 187–215.

[148] Feng Wang, Peng Ma, and Jianxin Guo. "Robust Cooperative Primary User Localization in Sensor Networks". In: *2020 International Conference on Virtual Reality and Intelligent Systems (ICVRIS)*. IEEE. 2020, pp. 848–851.

[149] Bernhard Etzlinger, Andreas Ganhör, Julian Karoliny, Richard Hüttner, and Andreas Springer. "WSN implementation of cooperative localization". In: *2020 IEEE MTT-S International Conference on Microwaves for Intelligent Mobility (ICMIM)*. IEEE. 2020, pp. 1–4.

[150] Yanjun Cao, David St-Onge, and Giovanni Beltrame. "Collaborative localization and tracking with minimal infrastructure". In: *2020 18th IEEE International New Circuits and Systems Conference (NEWCAS)*. IEEE. 2020, pp. 114–117.

[151] Chanxin Zhou and Bang Wang. "Online collaborative localization". In: *IEEE Internet of Things Journal* 8.4 (2020), pp. 2712–2721.

[152] Lukas Wielandner, Erik Leitinger, and Klaus Witrisal. "RSS-based cooperative localization and orientation estimation exploiting antenna directivity". In: *IEEE Access* 9 (2021), pp. 53046–53060.

[153] Ke Han, Chongyu Zhang, Huashuai Xing, and Yunfei Xu. "An area optimization based cooperative localization algorithm with node selection". In: *China Communications* 18.12 (2021), pp. 178–195.

[154] David Chiasson and Peter B. Shull. "Ultrawideband Ranging in Dynamic Dense Human Networks". In: *IEEE Transactions on Human-Machine Systems* 52.6 (2022), pp. 1327–1337.

[155] Bodhibrata Mukhopadhyay, Seshan Srirangarajan, and Subrat Kar. "RSS-Based Cooperative Localization and Edge Node Detection". In: *IEEE Transactions on Vehicular Technology* 71.5 (2022), pp. 5387–5403.

[156] Chanxin Zhou, Bang Wang, Yijun Mo, and Zeng Zeng. "MOCLoc: Emerging Online Collaborative Localization Enhanced by Multidimensional Scaling". In: *IEEE Transactions on Emerging Topics in Computational Intelligence* (2022).

[157] Bryan Teague, Zhenyu Liu, Florian Meyer, Andrea Conti, and Moe Z. Win. "Network Localization and Navigation With Scalable Inference and Efficient Operation". In: *IEEE Transactions on Mobile Computing* 21.6 (2022), pp. 2072–2087.

[158] Suwon Lee, Jae Hong Lee, Youdan Kim, and Chan Gook Park. "Information Fusion for Cooperative Indoor Positioning Using Bézier Curves". In: *IEEE Sensors Journal* 22.6 (2021), pp. 5063–5074.

[159] Yiming Ding, Zhi Xiong, Jun Xiong, Zhiguo Cao, and Wanling Li. "Distributed Collaborative Pedestrian Inertial SLAM With Unknown Initial Relative Poses". In: *IEEE Internet of Things Journal* 9.21 (2022), pp. 21632–21647.

[160] Lien-Wu Chen and Jun-Xian Liu. "Mobile Crowdsourced Guiding and Finding With Precise Target Positioning Based on Internet-of-Things Localization". In: *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 52.8 (2022), pp. 4849–4861.

[161] Pai Chet Ng, Petros Spachos, and Konstantinos Plataniotis. "COVID-19 and Your Smartphone: BLE-based Smart Contact Tracing". In: *arXiv preprint arXiv:2005.13754* (2020).

[162] Cheng Huang, Hao Liu, Wei Wang, and Jianyu Li. "A Compact and Cost-Effective BLE Beacon With Multiprotocol and Dynamic Content Advertising for IoT Application". In: *IEEE Internet of Things Journal* 7.3 (2019), pp. 2309–2320.

[163] TI Chowdhury, Md Mahbubur Rahman, Sadre-Ala Parvez, AKMM Alam, Abul Basher, Abusayeed Alam, and Shahriar Rizwan. "A multi-step approach for RSSi-based distance estimation using smartphones". In: *2015 International Conference on Networking Systems and Security (NSysS)*. IEEE. 2015, pp. 1–5.

[164] Fernando J. Aranda, Felipe Parralejo, Fernando J. Álvarez, and Joaquín Torres-Sospedra. "Multi-Slot BLE Raw Database for Accurate Positioning in Mixed Indoor/Outdoor Environments". In: *Data* 5.3 (2020), p. 67.

[165] Guoquan Li, Enxu Geng, Zhouyang Ye, Yongjun Xu, Jinzhao Lin, and Yu Pang. "Indoor positioning algorithm based on the improved RSSI distance model". In: *Sensors* 18.9 (2018), p. 2820.

[166] Xin-Yu Lin, Te-Wei Ho, Cheng-Chung Fang, Zui-Shen Yen, Bey-Jing Yang, and Feipei Lai. "A mobile indoor positioning system based on iBeacon technology". In: *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE. 2015, pp. 4970–4973.

[167] Jun-Ho Huh, Yohan Bu, and Kyungryong Seo. "Bluetooth-tracing RSSI sampling method as basic technology of indoor localization for smart homes". In: *Int. J. Smart Home* 10.10 (2016), pp. 1–14.

[168] Viktoriia Shubina, Aleksandr Ometov, and Elena Simona Lohan. "Technical perspectives of contact-tracing applications on wearables for COVID-19 control". In: *2020 12th International Congress on Ultra Modern Telecommunications and Control Systems and Workshops (ICUMT)*. IEEE. 2020, pp. 229–235.

[169] Jun-Ho Huh and Kyungryong Seo. "An indoor location-based control system using bluetooth beacons for IoT systems". In: *Sensors* 17.12 (2017), p. 2917.

[170] Qian Zhao, Yang Liu, Huiqiang Wang, Hongwu Lv, Guangsheng Feng, and Mao Tang. "A Cooperative Indoor Localization Method Based on Spatial Analysis". In: *International Conference of Pioneering Computer Scientists, Engineers and Educators*. Springer. 2018, pp. 628–637.

[171] Nadeem Ahmed, Regio A. Michelin, Wanli Xue, Sushmita Ruj, Robert Malaney, Salil S. Kanhere, Aruna Seneviratne, Wen Hu, Helge Janicke, and Sanjay K. Jha. "A survey of COVID-19 contact tracing apps". In: *IEEE access* 8 (2020), pp. 134577–134601.

[172] Germán Martín Mendoza-Silva, Miguel Matey-Sanz, Joaquín Torres-Sospedra, and Joaquín Huerta. "BLE RSS measurements dataset for research on accurate indoor positioning". In: *Data* 4.1 (2019), p. 12.

[173] Mehdi Mohammadi, Ala Al-Fuqaha, Mohsen Guizani, and Jun-Seok Oh. "Semisupervised deep reinforcement learning in support of IoT and smart city services". In: *IEEE Internet of Things Journal* 5.2 (2017), pp. 624–635.

[174] A. R. Jiménez, F. Seco, and J. Torres-Sospedra. "Tools for smartphone multi-sensor data registration and GT mapping for positioning applications". In: *2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. 2019, pp. 1–8.

[175] Juan D. Gutiérrez, Antonio R. Jiménez, Fernando Seco, Fernando J. Álvarez, Teodoro Aguilera, Joaquín Torres-Sospedra, and Fran Melchor. "GetSensorData: An extensible Android-based application for multi-sensor data registration". In: *SoftwareX* 19 (2022), p. 101186. URL: https://www.sciencedirect.com/science/article/pii/S2352711022001121.

[176] Google. *Android 5.0 APIs*. https://developer.android.com/about/versions/android-5.0 [Last visit: 02.11.2019].

[177] *GetSensorDataSuite*. https://gitlab.com/getsensordatasuite. 2021.

[178] Joaquín Torres-Sospedra, Raul Montoliu, Germán M Mendoza-Silva, Oscar Belmonte, David Rambla, and Joaquín Huerta. "Providing databases for different indoor positioning technologies: Pros and cons of magnetic field and Wi-Fi based positioning". In: *Mobile Information Systems* 2016 (2016).

[179] Joaquín Torres-Sospedra, Antonio R. Jiménez, Adriano Moreira, Tomás Lungenstrass, Wei-Chung Lu, Stefan Knauth, Germán Martín Mendoza-Silva, Fernando Seco, Antoni Pérez-Navarro, Maria João Nicolau, et al. "Off-line evaluation of mobile-centric indoor positioning systems: The experiences from the 2017 IPIN competition". In: *Sensors* 18.2 (2018), p. 487.

[180] Mohamed Hadi Habaebi, Rashid Omar Khamis, Alhareth Zyoud, and Md Rafiqul Islam. "RSS based localization techniques for ZigBee wireless sensor network". In: *2014 International Conference on Computer and Communication Engineering*. IEEE. 2014, pp. 72–75.

[181] Omotayo G. Adewumi, Karim Djouani, and Anish M. Kurien. "RSSI based indoor and outdoor distance estimation for localization in WSN". In: *2013 IEEE international conference on Industrial technology (ICIT)*. IEEE. 2013, pp. 1534–1539.

[182] Yisheng Miao, Huarui Wu, and Lihong Zhang. "The accurate location estimation of sensor node using received signal strength measurements in large-scale farmland". In: *Journal of Sensors* 2018 (2018).

[183] Zhenghua Chen, Qingchang Zhu, and Yeng Chai Soh. "Smartphone inertial sensor-based indoor localization and tracking with iBeacon corrections". In: *IEEE Transactions on Industrial Informatics* 12.4 (2016), pp. 1540–1549.

[184] L.A. Zadeh. "Fuzzy sets". In: *Information and Control* 8.3 (1965), pp. 338–353.

[185] Marwan Alakhras, Mourad Oussalah, and Mousa Hussein. "A survey of fuzzy logic in wireless localization". In: *EURASIP Journal on Wireless Communications and Networking* 2020 (2020), pp. 1–45.

[186] MA Hannan, Jamal Abd Ali, MS Hossain Lipu, A Mohamed, Pin Jern Ker, TM Indra Mahlia, M Mansor, Aini Hussain, Kashem M Muttaqi, and ZY Dong. "Role of optimization algorithms based fuzzy controller in achieving induction motor performance enhancement". In: *Nature communications* 11.1 (2020), pp. 1–11.

[187] Anh-Tu Nguyen, Tadanari Taniguchi, Luka Eciolaza, Victor Campos, Reinaldo Palhares, and Michio Sugeno. "Fuzzy control systems: Past, present and future". In: *IEEE Computational Intelligence Magazine* 14.1 (2019), pp. 56–68.

[188] Pavel Pascacio, Sven Casteleyn, and Joaquín Torres-Sospedra. *Supplementary Materials for 'Smartphone Distance Estimation Based on RSSI-Fuzzy Classification Approach'*. Version v1, 05.05.2021. Zenodo, May 2021. DOI: 10.5281/zenodo.4738405. URL: https://doi.org/10.5281/zenodo.4738405.

[189] Jie Yang and Yingying Chen. "Indoor localization using improved rss-based lateration methods". In: *GLOBECOM 2009-2009 IEEE Global Telecommunications Conference*. IEEE. 2009, pp. 1–6.

[190] Hanen Ahmadi, Federico Viani, Alessandro Polo, and Ridha Bouallegue. "An improved anchor selection strategy for wireless localization of WSN nodes". In: *2016 IEEE Symposium on Computers and Communication (ISCC)*. IEEE. 2016, pp. 108–113.

[191] Umair Mujtaba Qureshi, Zuneera Umair, Yaoxin Duan, and Gerhard Petrus Hancke. "Analysis of bluetooth low energy (ble) based indoor localization system with multiple transmission power levels". In: *2018 IEEE 27th International Symposium on Industrial Electronics (ISIE)*. IEEE. 2018, pp. 1302–1307.

[192] Shing H. Doong. "A closed-form formula for GPS GDOP computation". In: *GPS solutions* 13.3 (2009), pp. 183–190.

[193] Mahdia Tahsin, Sunjida Sultana, Tasmia Reza, and Md Hossam-E-Haider. "Analysis of DOP and its preciseness in GNSS position estimation". In: *2015 International conference on electrical engineering and information communication technology (ICEEICT)*. IEEE. 2015, pp. 1–6.

[194] Chuanyang Wang, Yipeng Ning, Jian Wang, Longping Zhang, Jun Wan, and Qimin He. "Optimized deployment of anchors based on GDOP minimization for ultra-wideband positioning". In: *Journal of Spatial Science* (2020), pp. 1–18.

[195] Omotayo Oshiga, Xiaowen Chu, Yiu-Wing Leung, and Joseph Ng. "Anchor selection for localization in large indoor venues". In: *2018 IEEE/ACM 26th International Symposium on Quality of Service (IWQoS)*. IEEE. 2018, pp. 1–6.

[196] Yung-Fa Huang, Wen Huang, You-Ting Jheng, Jong-Shin Chen, Chuan-Bi Lin, Yao-Jen Cheng, and Ching-Chuang Wei. "Indoor positioning with reference nodes selection in wireless networks". In: *2018 International Symposium on Computer, Consumer and Control (IS3C)*. IEEE. 2018, pp. 445–448.

[197] Tamer Dag and Taner Arsan. "Received signal strength based least squares lateration algorithm for indoor localization". In: *Computers & Electrical Engineering* 66 (2018), pp. 114–126.

[198] Paolo Barsocchi and Francesco Potorti. "Wireless Body Area Networks". In: *Wearable Sensors*. Elsevier, 2014, pp. 493–516.

[199] Yifeng Zhou, Jun Li, and Louise Lamont. "Multilateration localization in the presence of anchor location uncertainties". In: *2012 IEEE Global Communications Conference (GLOBECOM)*. IEEE. 2012, pp. 309–314.

[200] Jun Ma, Xuansong Li, Xianping Tao, and Jian Lu. "Cluster filtered KNN: A WLAN-based indoor positioning scheme". In: *2008 International Symposium on a World of Wireless, Mobile and Multimedia Networks*. IEEE. 2008, pp. 1–8.

[201] Korhan Cengiz. "Comprehensive Analysis on Least-Squares Lateration for Indoor Positioning Systems". In: *IEEE Internet of Things Journal* 8.4 (2020), pp. 2842–2856.

[202] Alessandro Montanari, Sarfraz Nawaz, Cecilia Mascolo, and Kerstin Sailer. "A study of bluetooth low energy performance for human proximity detection in the workplace". In: *2017 IEEE International Conference on Pervasive Computing and Communications (PerCom)*. IEEE. 2017, pp. 90–99.

[203] Pai Chet Ng, James She, and Rong Ran. "A compressive sensing approach to detect the proximity between smartphones and BLE beacons". In: *IEEE Internet of Things Journal* 6.4 (2019), pp. 7162–7174.

[204] Philipp H Kindt, Trinad Chakraborty, and Samarjit Chakraborty. "How reliable is smartphone-based electronic contact tracing for covid-19?" In: *Communications of the ACM* 65.1 (2021), pp. 56–67.

[205] Fazli Subhan, Asfandyar Khan, Sajid Saleem, Shakeel Ahmed, Muhammad Imran, Zubair Asghar, and Javed Iqbal Bangash. "Experimental analysis of received signals strength in Bluetooth Low Energy (BLE) and its effect on distance and position estimation". In: *Transactions on Emerging Telecommunications Technologies* (2019), e3793.

[206] Kang Eun Jeon, James She, Perm Soonsawad, and Pai Chet Ng. "Ble beacons for internet of things applications: Survey, challenges, and opportunities". In: *IEEE Internet of Things Journal* 5.2 (2018), pp. 811–828.

[207] Andreas Mathisen, Søren Krogh Sørensen, Allan Stisen, Henrik Blunck, and Kaj Grønbæk. "A comparative analysis of Indoor WiFi Positioning at a large building complex". In: *2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN)*. IEEE. 2016, pp. 1–8.

[208] Mikkel Baun Kjærgaard, Mads Vering Krarup, Allan Stisen, Thor Siiger Prentow, Henrik Blunck, Kaj Grønbæk, and Christian S Jensen. "Indoor positioning using wi-fi–how well is the problem understood?" In: *International Conference on Indoor Positioning and Indoor Navigation*. Vol. 28. 2013, p. 31.

[209] Joaquín Torres-Sospedra and Adriano Moreira. "Analysis of sources of large positioning errors in deterministic fingerprinting". In: *Sensors* 17.12 (2017), p. 2736.

[210] Yu-Chi Pu and Pei-Chun You. "Indoor positioning system based on BLE location fingerprinting with classification approach". In: *Applied Mathematical Modelling* 62 (2018), pp. 654–663.