
A Survey of Indoor Location Technologies and Methodologies

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Abstract

Indoor localization technologies have become indispensable in environments where traditional GPS systems are ineffective due to signal obstructions. This survey explores the advancements and methodologies in indoor positioning systems, emphasizing their applications in navigation, asset tracking, and spatial analytics. Key technologies include Wi-Fi fingerprinting, RFID, Ultra-Wideband (UWB), and Bluetooth Low Energy (BLE), each offering unique advantages and challenges. Wi-Fi fingerprinting is noted for its cost-effectiveness, while UWB provides high precision, making it suitable for applications requiring fine-grained localization. RFID systems are robust in object tracking but can be costly due to infrastructure needs. BLE offers a balance between accuracy and cost, although it may suffer from signal attenuation. The integration of machine learning, such as convolutional neural networks, enhances the precision of these systems, enabling them to adapt to dynamic environments. Privacy-preserving techniques, like Local Differential Privacy, are crucial for safeguarding user data. Future research directions include the development of hybrid systems that leverage multiple sensing modalities, advanced data processing frameworks, and privacy enhancements. These advancements promise to enhance the accuracy, efficiency, and adaptability of indoor localization systems, meeting the growing demands across various sectors. The survey underscores the transformative impact of these technologies, highlighting their critical role in improving operational efficiency and user experiences. As these technologies evolve, they are poised to offer greater precision and adaptability, ensuring their continued relevance and utility in diverse applications.

1 Introduction

1.1 Importance of Indoor Location Technologies

Indoor location technologies are essential in environments where conventional GPS systems fail due to signal blockages and interference, prompting the need for alternative localization solutions [1]. These technologies enhance real-time data processing capabilities, crucial for applications such as navigation and asset tracking in complex settings. The increasing demand for location-based services (LBSs) in indoor environments further underscores the necessity for robust indoor localization systems [2].

In healthcare, these technologies improve service delivery by enhancing the accuracy of real-time location systems, vital for patient tracking and resource management [3]. They also enrich user experiences in dynamic spaces like sports venues and museums, facilitating accessibility and precise positioning [4]. The need for reliable asset tracking in environments where GNSS-based solutions are inadequate drives the demand for precise indoor localization [1].

Indoor location technologies are critical across various sectors, including surveillance, navigation, robotics, and augmented reality, with computer vision methods gaining traction [2]. Techniques that create Fingerprint Maps (FM) of sensor signals are vital to meet the growing demand for

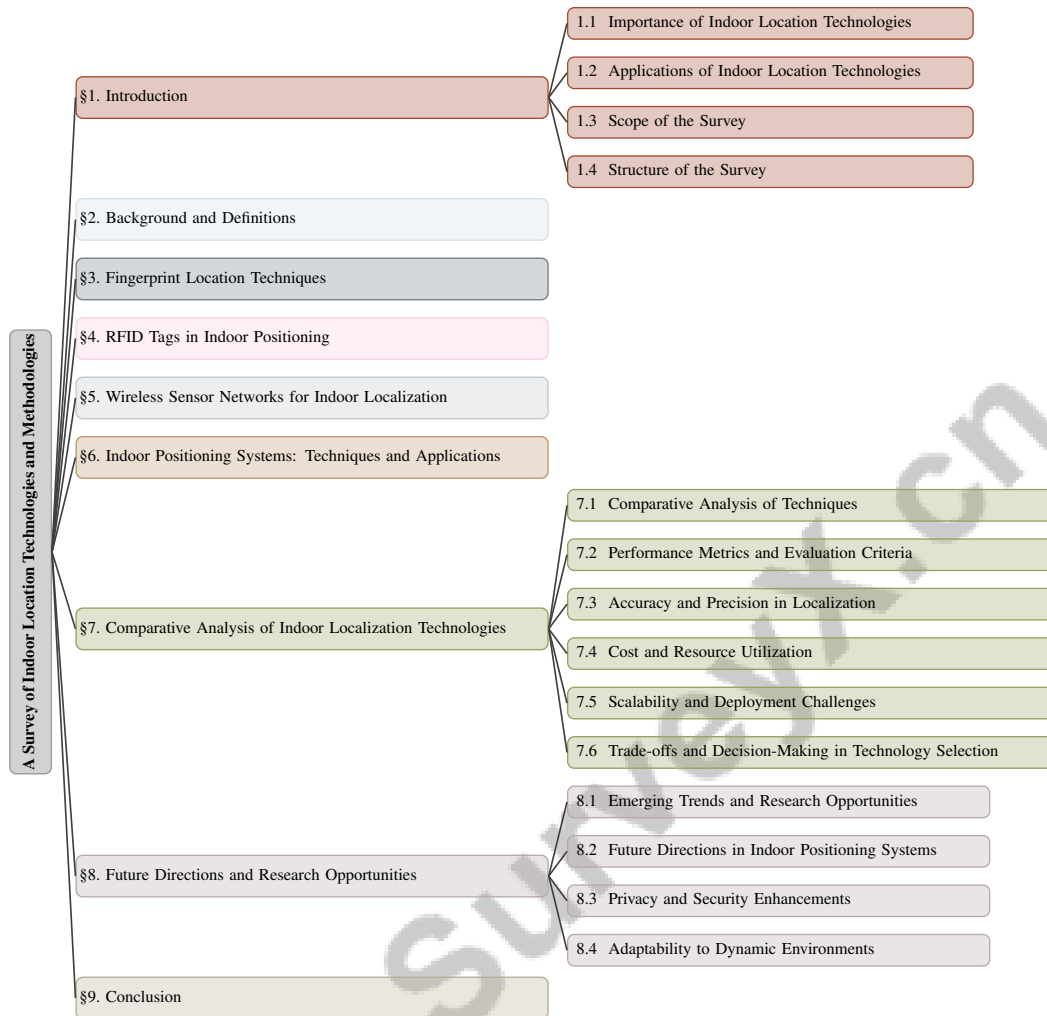


Figure 1: chapter structure

indoor localization services [1]. Additionally, visible light communication (VLC) systems provide high-speed, reliable positioning while supporting communication in indoor settings [4].

As individuals spend considerable time indoors, the significance of these technologies is amplified, impacting industries from healthcare to security and enhancing user experiences [5]. The challenge of accurately estimating indoor locations without specialized hardware highlights the need for scalable and environmentally sustainable solutions. Furthermore, the localization of Unmanned Aerial Vehicles (UAVs) in challenging environments, such as deep tunnels, exemplifies the critical need for effective indoor location technologies [3].

1.2 Applications of Indoor Location Technologies

Indoor location technologies are widely applied across various domains, significantly enhancing operational efficiency in complex environments. In healthcare, these technologies enable continuous patient monitoring and management by integrating physiological sensors into wearable devices, tracking parameters like stress and blood pressure while providing real-time location feedback [6]. This capability is crucial for improving patient outcomes and optimizing resource allocation within medical facilities.

In large venues such as university campuses, indoor positioning systems facilitate wayfinding, aiding individuals in navigating complex layouts. These systems provide insights into human mobility patterns, enhancing the design and functionality of spatial environments [7]. Indoor location

technologies also play a vital role in asset tracking, enabling precise monitoring of equipment and inventory, ensuring operational continuity, and reducing losses from misplaced assets.

Additionally, in high-occupancy environments, indoor location technologies contribute to advanced human activity recognition (HAR) systems that leverage sensor activations to identify individual actions, addressing challenges in multi-occupancy settings [5]. This capability is essential for applications in smart homes and offices, where personalized services and automation are increasingly sought.

The diverse capabilities of indoor location technologies, including radio-based location fingerprinting and various wireless techniques, are pivotal in modern infrastructure, enhancing user experiences and optimizing operational efficiencies. These technologies leverage existing radio infrastructures, such as WiFi and Bluetooth, to deliver accurate positioning services indoors, tackling challenges like client heterogeneity, scalability, and communication interference. Consequently, indoor localization systems are integral to sectors ranging from retail and healthcare to logistics, facilitating diverse applications driven by the Internet of Things (IoT) and ubiquitous connectivity [8, 9].

1.3 Scope of the Survey

This survey offers a comprehensive exploration of indoor localization technologies, emphasizing key advancements and methodologies that enhance precision and efficiency in various indoor environments. The limitations of traditional outdoor localization and mapping technologies, as noted by Shah et al., highlight the need for improved methods to infer indoor semantics [2]. In response, this survey investigates various indoor localization techniques, including Wi-Fi fingerprinting, which addresses the limitations of GPS and trilateration methods in indoor contexts.

The survey examines the integration of federated learning with fingerprint databases, exemplified by the FedLoc-AC algorithm, which mitigates heterogeneity issues in fingerprint data [10]. It also analyzes the role of RFID tags in indoor positioning, discussing their applications and challenges in dynamic environments [11]. Furthermore, non-RF sensing techniques, such as visible light, infrared, and electric field sensing, are explored for their passive localization capabilities [12].

Despite its inaccuracies in domestic settings, Bluetooth-based location sensing remains a significant aspect of indoor localization systems [13]. The survey discusses innovative techniques, including computer vision-based methods and Pedestrian Dead Reckoning (PDR), to address the shortcomings of traditional signal strength measurements [11]. It also tackles challenges like Non-Line-Of-Sight (NLOS) conditions in Ultra-Wideband (UWB) devices and proposes solutions for these issues [14].

Moreover, the integration of fall detection and indoor localization functionalities in cost-effective Ambient Assisted Living (AAL) systems is highlighted [15]. Smartphone-assisted solutions for indoor mapping, utilizing deep learning techniques to generate floor plans from point-clouds, are also examined [16]. Privacy concerns in indoor location technologies are addressed, with an emphasis on the Local Differential Privacy (LDP) framework as a novel approach for user privacy protection [4].

Innovative methodologies, such as a digital biomarker based on location eigenbehaviour data from contactless ambient sensors, further illustrate advancements in indoor location technologies [3]. This survey presents a holistic view of the current landscape of indoor localization technologies, offering insights into future research opportunities and technological advancements.

1.4 Structure of the Survey

The survey is systematically organized to provide a thorough analysis of indoor localization technologies, beginning with an introduction to their importance and applications across various sectors. Subsequent sections delve into core concepts and definitions essential for understanding indoor localization, including fingerprint location, RFID tags, wireless sensor networks, and indoor positioning systems. The survey explores fingerprint location techniques, discussing methodologies, advancements, and associated challenges.

Following this, the role of RFID tags in indoor positioning systems is analyzed, highlighting various technologies such as radio-based location fingerprinting and examining their applications, advantages, and limitations. This includes an exploration of their integration with existing wireless infrastructures like WiFi, as well as considerations of energy efficiency, scalability, tracking accuracy, and challenges

posed by heterogeneous client devices and communication interference [8, 17, 9]. The integration of wireless sensor networks in indoor localization systems is also discussed, addressing sensor technologies, data integration methods, and deployment challenges.

The survey further provides an overview of various indoor positioning systems, their techniques, applications, and challenges. A comparative analysis of indoor localization technologies evaluates performance, cost, scalability, and trade-offs, including the ANVIL framework, which employs a multi-head attention neural network to enhance localization accuracy [18].

Finally, the survey identifies emerging trends and future research opportunities in indoor localization, emphasizing potential advancements and enhancements in privacy and security. This structured approach facilitates a comprehensive analysis of the current landscape and future advancements in indoor localization technologies, encompassing a diverse range of methods such as computer vision, wireless techniques, and IoT integration, while evaluating their effectiveness in various applications including navigation, augmented reality, and robotics [19, 8, 17]. The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Indoor Localization

Indoor localization technologies have been developed to overcome GPS limitations in environments where signal obstructions and non-line-of-sight conditions are prevalent [11]. Fingerprint-based localization, which utilizes Wi-Fi and WLAN signals to estimate user positions through signal strength patterns, addresses challenges such as multipath propagation and environmental dynamics, thus enabling precise localization [20]. This method requires constructing extensive and accurate radio maps, traditionally a labor-intensive process [21]. Advances like federated learning, particularly the FedLoc-AC method, improve localization accuracy by addressing fingerprint data heterogeneity while ensuring user privacy [10].

Bluetooth Low Energy (BLE) is crucial in indoor positioning, providing real-time tracking and navigation through signal strength measurements [13]. However, BLE systems face challenges such as multipath interference and human body attenuation. RFID tags, which use radio frequency identification for object tracking, encounter issues like signal fluctuations and inadequate anchor deployment, impacting precision [22].

Wireless Sensor Networks (WSNs) offer a robust framework for integrating various sensor technologies, facilitating cooperative localization through multi-user measurements in areas with sparse anchor nodes [23]. Non-RF sensing methods, including visible light positioning and electric field sensing, enhance device-free localization (DFL) accuracy in complex indoor environments [12]. Local Differential Privacy (LDP) ensures user privacy by allowing local perturbation of location data before sharing [4].

Ultra-Wideband (UWB) technology is significant for efficient indoor localization, especially in overcoming Non-Line-Of-Sight (NLOS) conditions [24]. UWB systems are scalable, accommodating numerous active tags within a single network. The complexity of indoor environments, characterized by obstacles and dynamic conditions, complicates the design of effective positioning systems. Techniques like deep learning, including Recurrent and Convolutional Neural Networks, are used to generate indoor layouts and improve localization accuracy [16].

This survey categorizes methods based on technologies (e.g., Wi-Fi, UWB, RFID) and techniques (e.g., RSSI, ToF, AoA), highlighting their advantages and challenges [17]. The focus is on challenges and advancements in positioning, localization, and navigation technologies, especially for autonomous vehicles and complex environments [25]. Wi-Fi systems, for instance, use RSSI measurements to determine user location, enabling context-aware audio playback for artworks [26].

The diversity in indoor localization technologies and methodologies highlights the challenges of accurate location determination, particularly in crowded areas where GPS is ineffective [27]. Integrating frameworks like satellite-based and inertial navigation systems provides a comprehensive approach to these challenges. Mobile crowd sensing, which leverages data from citizen smartphones processed with machine learning, offers innovative solutions for accurate indoor localization [28].

Core concepts such as location eigenbehaviour and passive infrared sensor data are defined as crucial components for cognitive ability assessment [3].

In recent years, the field of indoor positioning systems has witnessed significant advancements, particularly in the development of fingerprint location techniques. These methodologies have evolved to include a variety of approaches, each contributing to the overall efficacy of positioning accuracy. Figure 2 illustrates the hierarchical structure of these techniques, categorizing them into three main groups: machine learning methods, probabilistic and dynamic techniques, and privacy and crowdsourced methods. This figure not only delineates these categories but also emphasizes recent advancements in both theoretical and practical enhancements, as well as innovations in machine learning and signal processing. By showcasing the progression and integration of diverse approaches, the figure underscores the ongoing efforts to refine and improve indoor positioning systems, ultimately leading to more reliable and efficient applications in various environments.

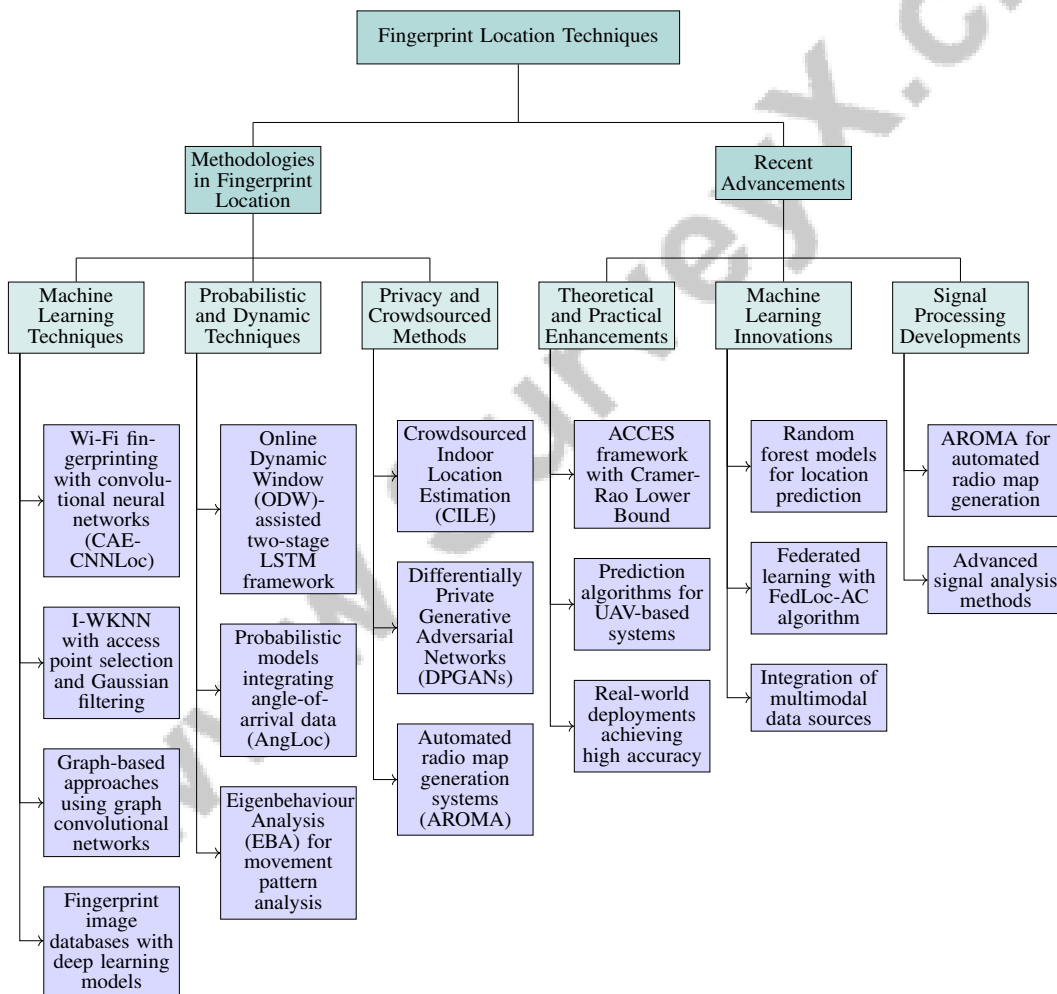


Figure 2: This figure illustrates the hierarchical structure of fingerprint location techniques, categorizing methodologies into machine learning, probabilistic and dynamic techniques, and privacy and crowdsourced methods. Additionally, it highlights recent advancements in theoretical and practical enhancements, machine learning innovations, and signal processing developments, showcasing the progression and integration of diverse approaches in improving indoor positioning systems.

3 Fingerprint Location Techniques

3.1 Methodologies in Fingerprint Location

Fingerprint-based localization methodologies are crucial for refining the precision and scalability of indoor positioning systems. Wi-Fi fingerprinting serves as a fundamental technique, leveraging unique Wi-Fi signal characteristics for location determination. Techniques like CAE-CNNLoc utilize convolutional neural networks to enhance localization accuracy by classifying locations based on Wi-Fi signal strengths [29]. The I-WKNN method improves upon the traditional Weighted K-Nearest Neighbors (WKNN) by incorporating access point selection and asymmetric Gaussian filtering to mitigate signal variability [29].

The Online Dynamic Window (ODW)-assisted two-stage LSTM framework exemplifies the application of dynamic windowing techniques to enhance real-time localization through temporal data analysis [30]. Graph-based approaches, such as the GCN-based indoor localization algorithm, employ graph convolutional networks to model access points and their interconnections, utilizing received signal strength indicators for precise localization [31]. Probabilistic models like AngLoc integrate angle-of-arrival data with probabilistic reasoning to boost positioning accuracy [32].

Automated radio map generation systems, such as AROMA, leverage ray tracing and diffraction theory to overcome the challenges of manual map construction [21]. Crowdsourced Indoor Location Estimation (CILE) methodologies harness Wi-Fi signal data from mobile devices, demonstrating the potential of collaborative data collection in advancing indoor positioning [28]. Privacy-preserving techniques, including Differentially Private Generative Adversarial Networks (DPGANs), generate synthetic indoor location data, balancing privacy with localization accuracy [33].

Fingerprint image databases constructed from Wi-Fi and magnetic field strength data utilize deep learning models for signal matching, enhancing localization precision [34]. The MetaRadar system, employing a metasurface-assisted approach, modifies radio channels to create diverse radio maps, further refining localization accuracy [35]. Eigenbehaviour Analysis (EBA) refines fingerprint location techniques by analyzing movement patterns derived from location data [3]. These methodologies, spanning machine learning, probabilistic models, crowdsourced data, and privacy-preserving techniques, collectively advance precise indoor positioning systems.

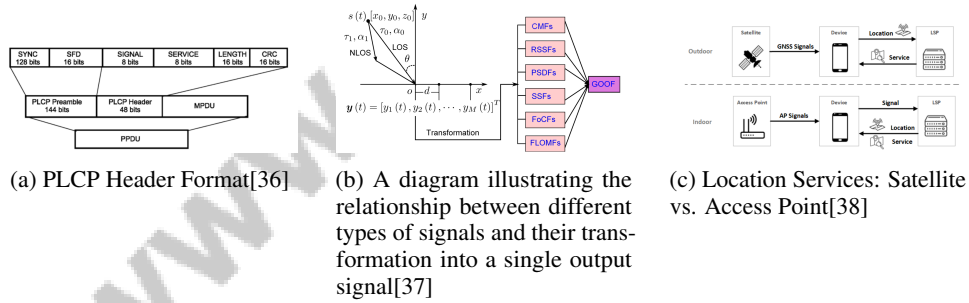


Figure 3: Examples of Methodologies in Fingerprint Location

As depicted in Figure 3, various methodologies in fingerprint location techniques are illustrated. Figure 1(a) shows the PLCP Header Format, integral to the IEEE 802.15.4 standard's Physical Layer, encapsulating the Physical Layer Data Unit (PLDU) for wireless transmission. Figure 1(b) illustrates the signal transformation process, depicting the integration of different signal types into a unified output. Figure 1(c) contrasts satellite and access point location services, revealing distinct communication pathways with Location Service Providers (LSPs). These examples collectively provide an insightful overview of the methodologies underpinning fingerprint location techniques, highlighting the intricate interplay of technology and signal processing in contemporary location services.

3.2 Recent Advancements

Recent advancements in fingerprint location techniques have notably improved the precision and adaptability of indoor positioning systems. The ACCES framework, utilizing the Cramer-Rao

Lower Bound for offline accuracy estimation, exemplifies a theoretical approach that expands the applicability of fingerprint systems across diverse environments [39]. Prediction algorithms addressing missing or zero flow values, particularly in UAV-based distance measurement systems, have enhanced accuracy in challenging conditions such as low-light environments [14].

As illustrated in Figure 4, these advancements can be categorized into three primary areas: theoretical approaches, machine learning applications, and automated systems. Each category encompasses key innovations and methods that have contributed to the precision and efficiency of indoor positioning systems.

Machine learning continues to significantly advance fingerprint location techniques. Random forest models have demonstrated effectiveness in enhancing location prediction accuracy, showcasing the potential of ensemble learning methods in refining indoor localization systems [20]. Federated learning, as demonstrated by the FedLoc-AC algorithm, addresses data heterogeneity, improving localization accuracy while preserving user privacy [10].

Innovative systems like AROMA automate radio map generation through ray tracing and diffraction theory, reducing the burdens of manual calibration and enhancing localization accuracy [21]. Real-world deployments of Wi-Fi-based systems, such as in museums, have achieved remarkable accuracy levels, with some reporting an average accuracy of 96.0

The evolution of fingerprint location techniques is characterized by the integration of multimodal data sources and advanced signal processing methods. These innovations, driven by advancements in data processing, machine learning, and signal analysis, collectively contribute to the development of more accurate and efficient indoor positioning systems, meeting the increasing demands for precision in complex indoor environments [1].

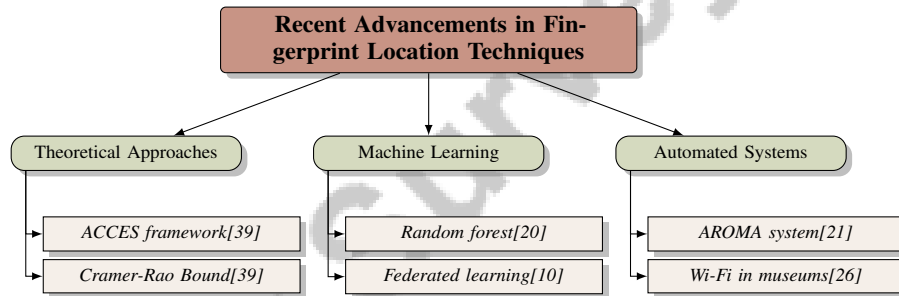


Figure 4: This figure illustrates the recent advancements in fingerprint location techniques, highlighting three primary categories: theoretical approaches, machine learning applications, and automated systems. Each category includes key innovations and methods that have contributed to the precision and efficiency of indoor positioning systems.

4 RFID Tags in Indoor Positioning

4.1 Introduction to RFID Technology in Indoor Positioning

RFID (Radio Frequency Identification) technology plays a crucial role in indoor positioning systems, offering real-time tracking and localization capabilities without the need for line-of-sight, unlike GPS. This feature makes RFID particularly suitable for indoor environments with common obstructions. By utilizing electromagnetic fields, RFID systems can automatically identify and track tags on objects, providing high accuracy and reliability essential for applications such as inventory management and asset tracking [11].

Recent advancements have focused on enhancing the accuracy and efficiency of indoor positioning by integrating RFID with other sensing modalities. For instance, combining RFID with ultrasonic sensing improves localization precision in environments where Wi-Fi signals might lack granularity [40]. Systems like UoMGuide utilize Bluetooth technology to implement modular architectures, further enhancing positioning accuracy [40].

RFID also augments existing Wi-Fi-based localization systems. Integrating RFID with Wi-Fi enhances localization precision, especially in settings with established Wi-Fi infrastructure, offering

a cost-effective means to improve accuracy [26]. Furthermore, RFID facilitates the creation of fingerprint databases using Received Signal Strength Indicator (RSSI) values for real-time positioning, involving comprehensive data collection to ensure reliability. Low-cost methods like QR codes complement RFID systems, enhancing user experience in indoor environments [27].

The integration of RFID with existing wireless infrastructures, such as Wi-Fi, enables precise location tracking while minimizing deployment costs. Its scalability effectively manages multiple heterogeneous clients, addressing challenges related to measurement interference and positioning accuracy. As indoor localization becomes increasingly vital across sectors like retail and tourism, RFID significantly enhances the efficiency, accuracy, and user experience of these systems [17, 41, 9, 42, 8]. The growing demand for accurate indoor localization underscores RFID's indispensable role in advancing these technologies.

4.2 Types of RFID Technologies and Their Applications

RFID technologies, encompassing active, passive, and semi-passive systems, cater to specific needs in indoor localization systems. A notable innovation is the use of a single mobile reader paired with a reference matrix, diverging from traditional methods that employ multiple fixed readers, allowing for more flexible and cost-effective deployments [43].

Active systems, with battery-powered tags that autonomously transmit signals, are suitable for real-time tracking over long distances in large areas like warehouses. Passive systems, reflecting signals from a reader without their own power source, are cost-effective for short-range applications, ideal for tracking assets in confined spaces such as offices or retail environments. Semi-passive systems, or battery-assisted passive systems, combine features of both, using a battery to power the tag's circuitry while relying on an external reader for communication. This hybrid approach enhances signal reliability and operational range, effectively addressing challenges like interference and positioning accuracy in indoor environments [43, 12].

Beyond asset tracking, RFID technologies are increasingly employed in personnel tracking, ensuring safety by monitoring movements within facilities. They are integral to modern inventory management, providing real-time stock information and precise item locations, thereby enhancing supply chain visibility and operational efficiency. Advancements such as 3D location algorithms and integration with other positioning systems further bolster inventory data accuracy, supporting smarter decision-making [9, 25, 44, 8, 43].

RFID is increasingly integrated with complementary localization technologies like Wi-Fi, Ultra Wideband (UWB), and Bluetooth, significantly enhancing indoor positioning systems' accuracy and functionality. This integration harnesses each technology's strengths, improving energy efficiency, scalability, and tracking precision while addressing the complexities of indoor localization [8, 43, 9, 17]. Combining RFID with Wi-Fi or Bluetooth offers a multi-layered approach that enhances precision in complex environments such as hospitals or airports, where accurate localization is critical for operational efficiency and safety.

The versatility of RFID technologies in indoor localization highlights their significance in modern infrastructure, providing scalable solutions tailored to diverse applications. As demand for accurate indoor localization services grows, particularly in the context of the Internet of Things (IoT), RFID technologies are essential in delivering reliable and efficient positioning solutions that enhance user experiences across various applications [8, 17].

4.3 Innovative Approaches to RFID-Based Localization

Innovative approaches to RFID-based localization have significantly improved the accuracy and efficiency of indoor positioning systems. Techniques employing a mobile RFID reader alongside a matrix of reference and virtual tags allow for flexible and cost-effective deployments, especially where multiple fixed readers are impractical. This mobile-reader approach enables systems to dynamically adapt to changing environments, enhancing localization accuracy [43].

As shown in Figure 5, which illustrates these innovative approaches to RFID-based localization, the utility of mobile RFID readers is emphasized alongside the application of Bayesian Surprise for enhanced navigation experiences. This latter method prioritizes areas deviating from expected patterns, offering more informative feedback for indoor navigation. Concentrating on these unexpected regions

delivers precise and contextually relevant localization information, enriching the user experience [45].

Furthermore, the integration of RFID with other sensor systems, exemplified by the Ambient Assisted Living (AAL) framework, showcases multi-sensor fusion's potential in improving indoor localization. The AAL-FDIL system incorporates smart cameras and wearable sensors to monitor user activities and locations in real-time, offering a comprehensive view of the indoor environment. This integration enhances localization accuracy and supports functionalities like fall detection and user activity monitoring, underscoring the versatility of RFID-based systems in real-world applications [15].

These innovative approaches reflect the ongoing evolution of RFID-based localization technologies, emphasizing flexibility, integration, and contextual awareness in developing effective indoor positioning solutions. As the demand for precise indoor localization escalates, advancements in techniques such as Angle of Arrival (AoA), Time of Flight (ToF), and Received Signal Strength (RSS) utilizing technologies like Wi-Fi, RFID, UWB, and Bluetooth will be crucial in meeting modern infrastructure's diverse requirements. These developments aim to improve accuracy, reliability, energy efficiency, cost-effectiveness, and scalability, playing a pivotal role in the evolution of location-based services in indoor environments [8, 17].

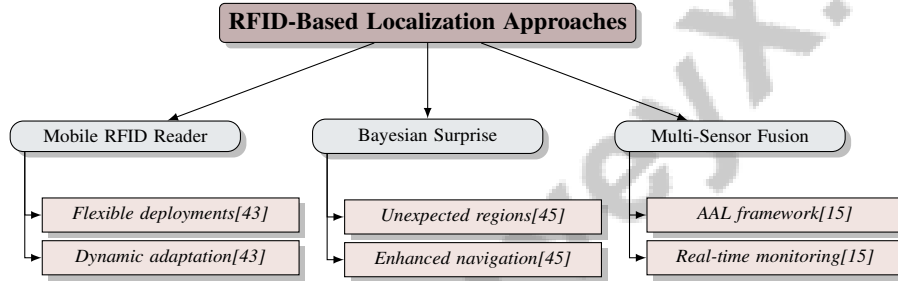


Figure 5: This figure illustrates the innovative approaches to RFID-based localization, highlighting the use of mobile RFID readers for flexible deployments, the application of Bayesian Surprise for enhanced navigation, and the integration of multi-sensor fusion within the Ambient Assisted Living framework for real-time monitoring.

4.4 Challenges and Limitations of RFID in Indoor Localization

Despite its advantages for indoor localization, RFID technology faces challenges and limitations hindering widespread adoption. Interference in metallic environments, such as shipyards, can degrade RFID system performance [44]. This challenge is compounded by the extensive infrastructure required, leading to increased costs and complexity. The need for multiple fixed readers to enhance accuracy further contributes to high implementation costs and logistical challenges [43].

Signal fluctuation is another major obstacle, particularly in SIOF-based methods, where signal variability in unknown indoor environments results in low accuracy and robustness [37]. RFID systems' sensitivity to environmental changes, including interference from electronic devices and structural variations, affects the reliability and consistency of localization results.

Integrating crowdsourced radio maps into existing localization frameworks is complicated by inherent noise and inaccuracies in location data, potentially undermining localization effectiveness [46]. Limited access to channel measurements from commercial mmWave chipsets restricts RFID-based systems' potential, as these measurements are critical for high localization accuracy [47].

Moreover, the cumulative error associated with IMU data and the significant computational power required for processing in IMU-based methodologies present challenges limiting RFID systems' scalability and efficiency in dynamic environments [30]. The WIPS method's reliance on the number and placement of access points can impact localization accuracy [26]. Addressing these challenges requires developing innovative solutions enhancing RFID technology's adaptability, accuracy, and cost-effectiveness in indoor localization, ensuring its viability across a wide range of applications.

5 Wireless Sensor Networks for Indoor Localization

5.1 Integration of Sensor Technologies

Integrating diverse sensor technologies is pivotal in enhancing indoor localization systems' accuracy and reliability. Ultra-Wideband (UWB) transceivers provide precise distance measurements, forming the backbone of many localization frameworks, especially in environments with multipath interference [48]. Complementarily, Bluetooth Low Energy (BLE) beacons are deployed to collect signal strength data, enabling accurate positioning with low power consumption and straightforward deployment [13].

WiFi fingerprinting is another essential technology. Techniques like CAE-CNNLoc process WiFi signal patterns on edge devices, improving localization performance while reducing latency [49]. Collecting Received Signal Strength Indicator (RSSI) values from multiple access points at specified reference points further illustrates WiFi infrastructure integration to enhance localization accuracy [29].

RFID technology is extensively applied in scenarios like smart pipes in shipyards, facilitating real-time asset location monitoring [44]. In experimental setups, deploying fixed RFID anchor nodes alongside mobile RFID tags allows for RSS and Pedestrian Dead Reckoning (PDR) data measurement, demonstrating RFID's versatility in dynamic environments [23].

The integration of Global Navigation Satellite System (GNSS) technology into indoor localization systems exemplifies innovative wireless signal usage to enhance positioning accuracy. Leveraging GNSS signal characteristics to detect attenuating environments refines location fingerprinting techniques, addressing traditional outdoor GNSS applications' limitations in indoor settings. Advanced methodologies, like deep learning, further enhance indoor positioning systems' precision and scalability [50, 9, 51]. This integration is beneficial in complex indoor settings where conventional localization methods may falter.

Thermal imagery processing emerges as a cutting-edge method for extracting orientation information, particularly in firefighting scenarios where traditional sensor data, such as GPS, often fails due to extreme conditions. This technique enhances situational awareness for first responders by utilizing thermal imaging cameras to navigate low-visibility environments, enabling effective orientation estimation and activity recognition through advanced techniques like optical flow-based video compasses and fused IMU data [52, 5]. This underscores the importance of integrating unconventional sensor modalities to address specific challenges in indoor localization.

Furthermore, processing physiological data via cloud computation, as seen in wearable health monitoring systems, emphasizes the role of sensor technologies in providing comprehensive insights beyond mere location data [6]. Generalized fingerprinting approaches based on multipath components further enhance localization accuracy, demonstrating the efficacy of advanced signal processing techniques in refining indoor positioning systems.

The integration of WiFi infrastructure is vital for enhancing accuracy while minimizing the need for additional hardware, as evidenced by methods leveraging existing WiFi networks to improve localization without extensive new installations [28]. Techniques such as synthetic data generation using DPGAN ensure privacy while maintaining data utility in localization systems.

5.2 Data Integration and Processing Methods

Data integration and processing are crucial for enhancing indoor localization systems' accuracy and reliability within wireless sensor networks. The Dynamic Parallel Processing Framework (DPPF) exemplifies an approach that optimizes data integration and processing, significantly improving localization accuracy by efficiently managing the vast data generated by wireless sensor networks [9]. This framework enables concurrent processing of diverse data streams, reducing latency and enhancing responsiveness to dynamic environmental changes.

Figure 6 illustrates the hierarchical structure of data integration and processing methods in indoor localization systems, highlighting key frameworks, challenges, and application areas. It emphasizes the importance of advanced algorithms and frameworks like Dynamic Parallel Processing, Enhanced Optical Flow, and Bayesian Surprise Analysis in overcoming challenges such as poor lighting and

unexpected spatial structures, while showcasing applications in real-time tracking, augmented reality, and robotics.

Advanced predictive algorithms further refine distance estimation in challenging environments characterized by poor lighting and minimal surface features. The synergy between optical flow sensors and these algorithms enables precise distance measurements, even in traditionally challenging conditions for accurate localization [14]. This collaboration underscores the importance of robust data processing methods in overcoming conventional localization limitations.

Recognizing and adapting to surprising spatial structures significantly enhances localization accuracy. Evaluating method performance in real-world applications allows systems to dynamically adapt to learned structures, improving their ability to respond to unexpected spatial configurations [45]. This adaptability is essential for developing indoor localization systems that maintain high accuracy in diverse and evolving environments.

These data integration and processing methods illustrate ongoing advancements in indoor localization technologies, emphasizing the need for innovative frameworks and algorithms to manage complex data generated by modern sensor networks effectively. As indoor environments grow increasingly dynamic, particularly with applications in augmented reality, robotics, and navigation, the importance of advanced data processing techniques in improving localization accuracy is set to escalate. These techniques encompass methods including computer vision-based approaches utilizing static and mobile cameras, as well as technologies like RFID and Wi-Fi, crucial for accurately tracking mobile entities in real time. Consequently, developing and refining these data processing methods will be vital for enhancing indoor localization systems' effectiveness and reliability across various applications [41, 19].

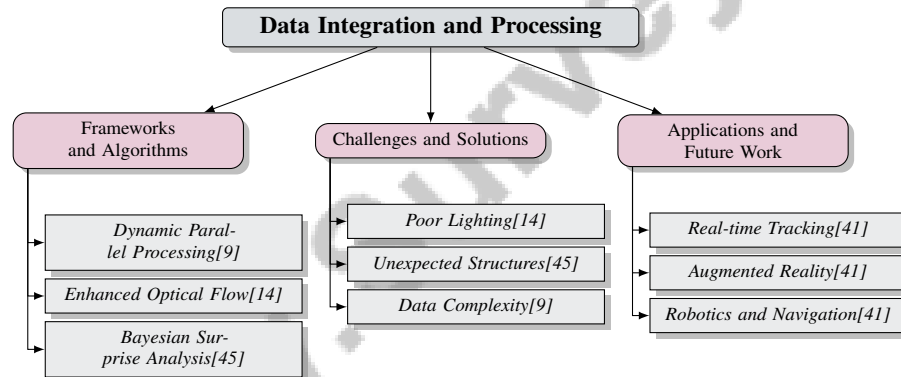


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5.3 Challenges in Sensor Network Deployment

Deploying sensor networks for indoor localization presents several challenges, particularly in complex environments with variable conditions. A significant challenge is the high average error in tag localization, especially along the x-axis with mobile RFID readers, as noted in studies on localization systems [43]. This issue is compounded by the dynamic nature of indoor spaces, where obstacles and varying signal propagation conditions can greatly affect localization accuracy.

Deploying sensor networks in harsh environments, such as shipyards, introduces additional complexities. The performance of RFID systems can be severely impacted by metallic surfaces and signal interference, necessitating further research to optimize RFID technology for such challenging conditions [44]. Moreover, integrating additional sensor technologies and developing advanced data analytics capabilities are crucial for enhancing system performance and reliability in demanding environments.

Addressing these challenges requires innovative solutions that enhance the adaptability and accuracy of sensor networks. Integrating various sensor modalities, such as combining Radio Frequency Identification (RFID) with complementary technologies like Wi-Fi and Bluetooth, enhances indoor localization systems by overcoming limitations inherent in single-technology approaches. Recent methodologies have demonstrated improved accuracy in detecting user locations by leveraging data from BLE beacons and scanners, in addition to accelerometer and gyroscope sensors, achieving performance accuracies exceeding 81

Overcoming the challenges in deploying sensor networks for indoor tracking necessitates a multi-faceted approach that combines technological innovation with robust data analytics and integration strategies. As research in indoor localization technology progresses, the anticipated development of more resilient and precise localization systems aims to address the increasing demands of complex indoor environments. This evolution is driven by the growing prevalence of IoT applications and the need for accurate positioning across various domains, including augmented reality, robotics, and navigation. Recent literature highlights a variety of techniques, such as Angle of Arrival (AoA), Time of Flight (ToF), and computer vision methods, which leverage diverse wireless technologies like Wi-Fi, RFID, and Ultra Wideband (UWB) to enhance localization accuracy and reliability. Ongoing evaluations of these systems focus on critical factors such as energy efficiency, cost, latency, and scalability, paving the way for innovative solutions that can effectively meet the challenges posed by intricate indoor settings [19, 8].

6 Indoor Positioning Systems: Techniques and Applications

The study of methodologies in indoor positioning systems (IPS) is crucial for improving localization precision and reliability. This section outlines the core concepts and technological advancements that support IPS, highlighting their operational principles and significance.

6.1 Overview of Indoor Positioning Systems

Indoor positioning systems (IPS) are indispensable in areas where GPS is ineffective due to signal obstructions, utilizing various methods to provide precise location data for applications such as navigation and asset tracking. The integration of Ultra-Wideband (UWB) with deep learning has significantly enhanced accuracy compared to traditional methods [25]. Techniques like CAE-CNNLoc use existing infrastructure and crowdsourced data for accurate localization without additional sensors, enhancing accuracy and reducing latency [4, 53]. The DPGAN framework generates synthetic indoor location data with differential privacy, addressing privacy concerns [33, 38]. Advanced fingerprint optimization methods, such as I-WKNN, achieve high success rates for deviations below 2 meters [29]. The AROMA method enhances IPS by providing accurate radio maps that adapt to environmental changes [21]. Frameworks like AAL integrate fall detection with localization, showcasing innovative IPS applications [15]. Comparative analyses by Kunthoth et al. highlight the diverse strategies in IPS, from machine learning to privacy-preserving techniques, contributing to the evolution of precise indoor positioning systems [11]. Ongoing advancements in IPS technologies underscore their critical importance in contemporary infrastructure, providing scalable solutions to meet the growing demand for precision in indoor localization [20, 8, 38, 17].

6.2 Techniques in Indoor Positioning Systems

IPS employ various techniques to achieve high accuracy where GPS is ineffective. Signal strength analysis, particularly through Received Signal Strength (RSS) measurements, exemplifies this approach, with methods like SVBI reducing Root Mean Square Error (RMSE) significantly [54]. The ODW-LSTM framework processes Inertial Measurement Unit (IMU) data with LSTM networks, enhancing real-time localization accuracy [30]. Audio-based techniques leverage ambient sound to extract features for room characterization, employing models like Gaussian Mixture Models (GMM) and Support Vector Machines (SVM) [2]. These methodologies address challenges like signal interference and accuracy demands, improving indoor navigation effectiveness across applications [36, 9, 41, 50, 8].

6.3 Applications and Real-World Implementations

IPS have extensive applications across sectors, demonstrating versatility in real-world implementations. In healthcare, IPS monitor patient movements and manage equipment, enhancing efficiency and care. Wearable health systems integrate physiological sensors for tracking vitals and location, providing critical data for timely interventions [6]. In education, IPS facilitate navigation and resource management on campuses, with systems like MazeMap improving accessibility and user experience [7]. Retail environments use IPS for asset tracking and customer engagement, leveraging technologies like RFID and Bluetooth beacons for real-time inventory monitoring and navigation [13, 55, 9, 38]. Museums enhance visitor experiences with context-aware audio guides, using Wi-Fi systems for precise content delivery [26]. In industrial settings, RFID-based systems track equipment and personnel, optimizing workflow and safety in large environments like shipyards [44]. These implementations highlight IPS adaptability across industries, enhancing operational efficiency and safety. As these systems evolve, they are expected to enhance functionality across sectors, with the indoor PLAN market projected to grow significantly, driven by innovations and smart technologies [56, 25, 44].

6.4 Challenges and Solutions in Indoor Positioning

IPS face challenges impacting accuracy and reliability, necessitating innovative solutions. The dynamic nature of indoor environments complicates the creation of accurate fingerprint maps, requiring advancements in Wi-Fi fingerprinting and assistive technologies [55]. Variability in radio environments, due to multipath propagation and user interference, further complicates consistent localization performance [35]. Efficient data management is crucial for real-time processing, posing significant challenges [50, 9]. Privacy concerns regarding data protection are critical, with frameworks like Local Differential Privacy (LDP) addressing these challenges [4]. In domestic environments, contextual interaction complexities pose additional challenges, as existing technologies may not support unique home characteristics [13]. Scalability is a concern, particularly in multi-label classification environments, requiring automation techniques like AROMA to streamline the fingerprinting process [21].

Figure 7 illustrates the primary challenges and solutions in indoor positioning systems (IPS), categorized into technological challenges, privacy concerns, and scalability issues. Each category highlights key aspects and references significant works addressing these challenges. Addressing these challenges requires a multifaceted approach combining technological innovation with advanced data processing strategies. By leveraging automation, deep learning, and scalable frameworks, IPS can overcome traditional limitations, enhancing indoor location-based services and improving user experiences while managing privacy concerns [16, 57, 58, 38].

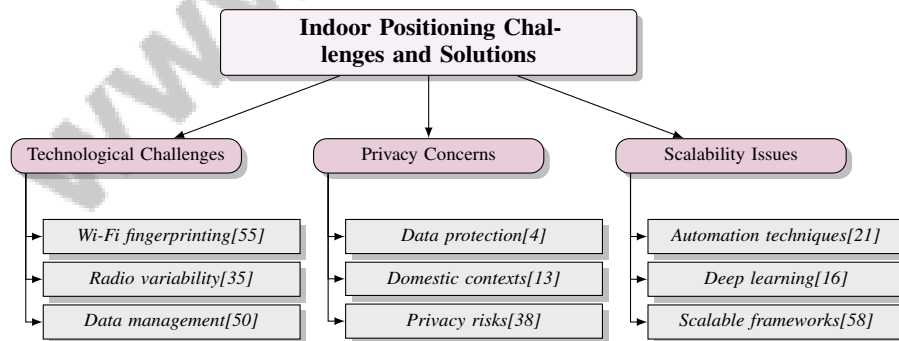


Figure 7: This figure illustrates the primary challenges and solutions in indoor positioning systems (IPS), categorized into technological challenges, privacy concerns, and scalability issues. Each category highlights key aspects and references significant works addressing these challenges.

7 Comparative Analysis of Indoor Localization Technologies

The demand for precise indoor localization necessitates a thorough examination of existing technologies, highlighting their strengths and limitations to inform practical applications. The subsequent

subsection, **Comparative Analysis of Techniques**, delves into methodologies employed in indoor localization, focusing on accuracy, computational complexity, and deployment costs, which are vital for informed decision-making.

7.1 Comparative Analysis of Techniques

Indoor localization techniques exhibit varied performance, computational demands, and cost implications. Wi-Fi fingerprinting is notable for its cost-effectiveness and high accuracy, particularly in cost-sensitive environments [1]. Cooperative localization enhances accuracy by utilizing shared user data, effectively mitigating errors in complex settings through collective fingerprint maps derived from sensors like Wi-Fi and Bluetooth [17, 39, 19, 42, 8].

Multimodal approaches, integrating diverse sensor inputs, overcome single-modality limitations, enhancing system robustness. Techniques combining Wi-Fi, Bluetooth, and magnetic signals with deep learning improve IPS reliability, addressing traditional GPS limitations [50, 8, 39, 9].

DALIS offers a cost-effective alternative for GPS-obstructed environments, using mobile devices or low-cost beacons to enhance user experience without extensive infrastructure [50, 59, 60, 38]. Inaudible audio-based techniques, using ultrasonic sensing, provide superior accuracy and privacy in device-free positioning scenarios [61, 12].

Advanced signal processing, such as distributed massive MIMO, achieves centimeter-level precision, leveraging high angular resolution and sophisticated algorithms like SAGE. Generalized fingerprinting systems further enhance accuracy with minimal training data [62, 9]. This analysis underscores the need to evaluate performance metrics, including accuracy, complexity, and costs, with continuous innovation essential to meet the growing demand for reliable indoor localization [25, 8, 9].

7.2 Performance Metrics and Evaluation Criteria

Benchmark	Size	Domain	Task Format	Metric
MazeMap[7]	20,000	Indoor Navigation	Wayfinding	Frequency of Requests, Spatial Distribution

Table 1: Table ef presents a summary of representative benchmarks used in the evaluation of indoor navigation systems. It includes key attributes such as the benchmark name, dataset size, domain of application, task format, and evaluation metrics, providing a comprehensive overview for assessing system performance.

Evaluating indoor localization technologies involves metrics such as accuracy, cost, energy efficiency, range, latency, scalability, and precision, crucial for applications in sectors like retail and healthcare [41, 8, 17]. Accuracy is assessed by metrics like RMSE, reflecting system precision. Robustness to environmental changes and scalability in high-density settings are critical, as is computational efficiency for real-time processing on mobile devices [35, 58]. Table 1 offers a detailed overview of representative benchmarks relevant to the performance evaluation of indoor localization technologies, highlighting the essential criteria used to assess their effectiveness.

Infrastructure costs influence adoption, with Wi-Fi systems being more cost-effective due to existing networks [1]. Privacy and security are increasingly important, with LDP frameworks safeguarding sensitive data [4]. Adaptability and integration with IoT devices are vital for long-term viability [13].

7.3 Accuracy and Precision in Localization

Accuracy and precision are crucial for effective indoor localization. Wi-Fi fingerprinting achieves high accuracy using signal strength patterns, enhanced by CNNs adapting to environmental changes [1]. UWB provides centimeter-level precision, beneficial for applications needing fine-grained localization, such as robotics [24, 25].

BLE beacons offer a balance between accuracy and cost, with techniques like Kalman filters mitigating signal attenuation [13]. RFID systems, integrated with Wi-Fi and IMUs, enhance precision by compensating for signal variability [11]. Hybrid systems combining multiple techniques utilize sensor fusion to achieve high accuracy in dynamic environments [35].

7.4 Cost and Resource Utilization

Cost and resource utilization are critical for the feasibility of indoor localization technologies. Wi-Fi fingerprinting is favored for low cost and minimal infrastructure, leveraging existing networks [1]. BLE beacons offer a cost-effective solution with low power consumption, though initial hardware costs must be considered [13].

RFID systems incur higher costs due to specialized equipment but are robust in challenging environments [11, 44]. UWB's high precision justifies its higher costs in precision-demanding applications [24]. Hybrid systems optimize resource utilization but may increase complexity and costs [35].

7.5 Scalability and Deployment Challenges

Scalability and deployment challenges affect the adoption of indoor localization systems. High infrastructure costs for RFID and UWB systems limit scalability, while Wi-Fi-based systems require labor-intensive fingerprint maps [44, 21]. Managing large data volumes from dense networks demands advanced processing frameworks [9]. Figure 8 illustrates the primary challenges in scalability and deployment for indoor localization systems, focusing on infrastructure costs, data management, and interoperability and privacy issues. It highlights the high costs associated with RFID, UWB, and Wi-Fi systems, the necessity for advanced data processing frameworks, and the critical importance of standardized protocols and privacy-preserving techniques.

Dynamic environments require systems to adapt to fluctuating conditions, necessitating robust algorithms [35]. Interoperability challenges arise with diverse technologies, requiring standardized protocols [58]. Privacy concerns necessitate LDP implementation, although it adds computational overhead [4].

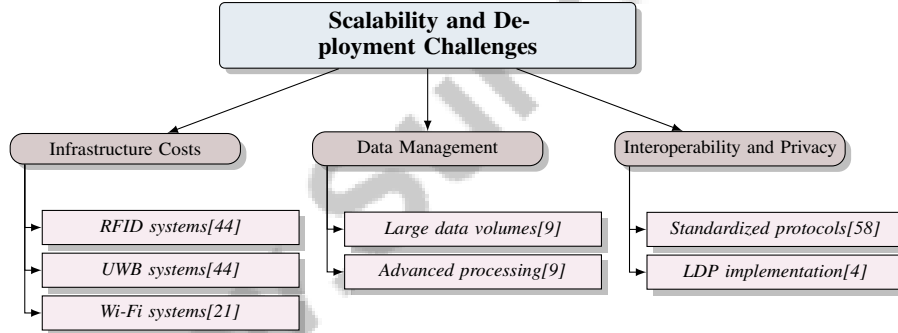


Figure 8: This figure illustrates the primary challenges in scalability and deployment for indoor localization systems, focusing on infrastructure costs, data management, and interoperability and privacy issues. It highlights the high costs of RFID, UWB, and Wi-Fi systems, the need for advanced data processing frameworks, and the importance of standardized protocols and privacy-preserving techniques.

7.6 Trade-offs and Decision-Making in Technology Selection

Selecting indoor localization technology involves weighing trade-offs among accuracy, cost, scalability, adaptability, energy efficiency, range, and latency. Wi-Fi fingerprinting is cost-effective with minimal infrastructure but requires extensive map maintenance. UWB offers superior accuracy at higher costs, suitable for precision-demanding applications [24, 25].

BLE beacons provide moderate accuracy and ease of deployment, influenced by environmental conditions [13]. RFID systems are preferred for reliability in complex settings, despite higher costs [1, 8, 9]. Hybrid systems achieve high accuracy but with increased complexity [35].

Decision-making must consider application-specific requirements, environmental conditions, and financial constraints, ensuring the selected technology meets operational goals effectively [41, 8]. Careful evaluation of these factors enables stakeholders to choose suitable indoor localization solutions.

8 Future Directions and Research Opportunities

The progression of indoor localization demands an in-depth analysis of factors influencing its evolution. This section explores emerging trends and research opportunities in indoor positioning technologies, highlighting key areas for innovation, particularly through the integration of advanced algorithms and machine learning.

8.1 Emerging Trends and Research Opportunities

Current trends in indoor localization focus on incorporating advanced algorithms and machine learning to boost system accuracy and flexibility. Enhancements in filtering and adaptive signal processing are crucial for refining Wi-Fi-based positioning [29]. Crowdsourced data collection is becoming prevalent, utilizing the widespread use of mobile devices to amass extensive datasets for machine learning applications. Hybrid systems that combine various technologies offer promising research paths to improve energy efficiency and address challenges in complex indoor environments [11]. Integrating additional sensor data and exploring machine learning techniques are essential for achieving robust localization in dynamic settings [12]. Future research should focus on merging deterministic and probabilistic methods, leveraging crowdsourcing for data collection, and exploring new physical media for positioning [1].

Advanced sensor fusion techniques, particularly in conjunction with emerging technologies, present significant opportunities for improving localization accuracy and robustness. Hybrid approaches that integrate multiple sensing techniques are promising directions for more accurate indoor positioning systems [12]. Future studies should also optimize computation strategies and explore effective aggregation methods to enhance localization performance [10].

Privacy concerns remain critical, with research investigating improvements in privacy guarantees through frameworks like Local Differential Privacy (LDP). This includes applying LDP techniques to enhance user privacy in trajectory data, indicating trends in privacy-preserving indoor localization [4].

Future research will focus on collecting larger datasets from multi-occupancy environments and enhancing models to account for time intervals in interactions, crucial for advanced human activity recognition systems [5]. Opportunities also exist in enhancing models to detect additional spatial objects, such as doors and windows, indicating advancements in indoor mapping technologies [16]. Expanding datasets with diverse room types and integrating additional modalities, such as visual and sensory data for enhanced semantic inference, are promising research directions [2].

In healthcare, the use of non-intrusive methods for cognitive ability monitoring highlights the potential of indoor localization technologies in health applications, showcasing an emerging trend in leveraging these technologies for health monitoring [3]. These trends and opportunities promise to advance the functionality of indoor localization systems across various domains, underscoring the importance of technological innovation and interdisciplinary collaboration.

8.2 Future Directions in Indoor Positioning Systems

Future advancements in indoor positioning systems aim to significantly enhance accuracy, efficiency, and applicability across diverse environments. Key areas of focus include optimizing channel estimates through advanced post-processing techniques, which are critical for improving location estimate precision in complex indoor settings [36]. Enhancing computational efficiency in signal recovery methods, particularly in autonomous frameworks (AuF), is another promising direction, leading to faster and more reliable signal processing essential for real-time applications [63]. Additionally, improving the robustness of fingerprint databases and developing adaptive algorithms responsive to changing indoor environments will further enhance system resilience and accuracy [64].

Integrating reinforcement learning and deep neural networks presents a novel approach for enhancing situational awareness, especially in dynamic environments like firefighting scenarios, yielding more intelligent and responsive indoor positioning systems [52]. Future research will also aim to unify indoor-outdoor classification with floor-level prediction, improving overall performance in contexts such as emergency response and navigation [56]. Refining algorithms for greater accuracy will

expand applications beyond traditional settings, such as shopping malls, to other complex indoor environments [60].

Exploring additional data sources and integrating wireless technologies, such as WLAN access points, into existing systems will enhance the accuracy and functionality of indoor positioning solutions [40]. Optimizing latent space dimensions and exploring new applications of models like SVBI in varied indoor environments will further advance indoor positioning technologies [54]. Improving the robustness of Wi-Fi fingerprinting methods against unseen locations and optimizing their performance on edge devices are critical future research areas, ensuring that indoor positioning systems remain effective and efficient in real-world applications [49]. Enhancing robustness in diverse indoor environments and integrating additional data sources will further improve positioning accuracy and reliability [65].

The future directions highlighted in recent studies underscore the critical role of technological innovation—such as advanced sensors, artificial intelligence, and IoT integration—and interdisciplinary collaboration in enhancing indoor positioning systems. This evolution responds to the increasing demand for accurate indoor localization services, projected to reach 28.2 billion by 2024, addressing challenges like signal fluctuations and hardware variability [9, 22, 25, 11, 8]. By overcoming current limitations and exploring new opportunities, researchers can develop more accurate

8.3 Privacy and Security Enhancements

Privacy and security in indoor localization systems are paramount, particularly in sensitive domains like healthcare and security monitoring. The integration of Indoor Positioning Systems (IPS) raises significant privacy concerns due to potential exposure of sensitive user location data to Location Service Providers (LSP) and adversaries. Robust privacy-preserving mechanisms, including Local Differential Privacy (LDP), are crucial for anonymizing user location data at the device level before transmission, safeguarding personal information from unauthorized access [4, 38]. As indoor localization technologies advance, the volume of sensitive location data processed increases, necessitating stringent privacy and security measures to maintain user trust.

Developing privacy-preserving mechanisms that ensure accurate localization while protecting user data is a primary challenge. Techniques like LDP enable users to locally perturb their location data before sharing, ensuring sensitive information remains protected even if the data aggregator is compromised [4]. Incorporating privacy-preserving algorithms into indoor localization systems enhances user privacy without sacrificing accuracy.

The integration of advanced encryption methods and secure data transmission protocols is essential for safeguarding location data from interception and tampering during communication between devices and servers. Implementing privacy-preserving mechanisms, such as LDP, can enhance security by altering location data at the user's device before transmission, preventing unauthorized access by LSPs and potential adversaries [4, 38]. Ensuring end-to-end encryption and employing secure authentication mechanisms can significantly mitigate the risk of data breaches.

Access control management is another critical aspect of privacy and security in indoor localization. Implementing robust access control policies is vital for safeguarding sensitive location data, ensuring that only authorized personnel can access this information. This not only reduces the risk of data misuse but also enhances user confidence in the system's security. Incorporating advanced privacy-preserving techniques, like LDP and cryptographic methods, further protects user data from unauthorized access and potential adversaries [59, 4, 27, 38].

As indoor localization systems continue to evolve, addressing privacy and security concerns will remain a priority. Future research should focus on developing innovative privacy-preserving techniques and security frameworks adaptable to the dynamic nature of indoor environments and diverse application requirements. By enhancing privacy and security features, indoor localization systems can facilitate widespread adoption while providing dependable, secure, and privacy-sensitive solutions across various sectors. This approach addresses critical privacy risks inherent in indoor location fingerprinting, where sensitive data from user devices is accessed by LSPs and potential adversaries. Implementing privacy-preserving mechanisms—such as cryptographic techniques, anonymization, differential privacy, and federated learning—can mitigate these vulnerabilities, improving user trust and enabling broader applications in industries leveraging IoT technologies [42, 8, 38].

8.4 Adaptability to Dynamic Environments

The effectiveness of indoor localization systems across various applications heavily relies on their adaptability to dynamic environments, such as transitions from outdoor GPS-enabled areas to indoor or obstructed spaces. This adaptability is crucial, as existing infrastructure-based systems often face challenges like high installation costs, reliability issues, latency, and poor localization accuracy in frequently changing conditions. Recent advancements propose novel, distributed, and adaptive mechanisms utilizing collaborative techniques and low-cost reference nodes to enhance localization accuracy and efficiency, addressing the limitations of traditional systems [59, 8]. Indoor environments are inherently dynamic, characterized by frequent changes in layout, occupancy, and signal conditions, necessitating rapid and accurate adaptation to maintain high accuracy and reliability.

Future research could enhance the adaptability of existing methods by integrating advanced machine learning algorithms capable of real-time learning and adaptation to environmental changes. Such algorithms could dynamically adjust localization parameters based on current conditions, improving responsiveness and accuracy. Additionally, investigating alternative tensor completion techniques offers a promising avenue for mitigating the impact of anomalies common in dynamic environments [66].

Integrating adaptive filtering processes and real-time data processing frameworks is essential for enhancing adaptability. Leveraging these technologies enables systems to continuously update models and parameters in response to environmental changes, ensuring consistent performance despite significant variability. This approach is particularly beneficial in dynamic environments characterized by high human activity or frequent structural changes, where conventional static models often fail. For instance, innovative systems utilizing smartphone sensor data can accurately determine a user's floor level in tall buildings without relying on beacons, achieving 100

Developing hybrid localization systems that combine multiple sensing modalities can enhance adaptability by providing redundant and complementary data sources. This redundancy ensures sustained accuracy, even if one data source becomes unreliable due to environmental changes, such as signal attenuation indoors or obstructions like tall buildings interfering with GPS signals. By leveraging multiple data sources, including GNSS signals and smartphone sensor data, systems can automatically detect and adapt to varying conditions, maintaining reliable performance across diverse scenarios [56, 2, 59, 51]. Sensor fusion techniques can intelligently integrate data from various sources to produce more robust and accurate localization results.

To effectively enhance adaptability to dynamic environments, a comprehensive strategy is essential, integrating sophisticated algorithms, real-time data processing techniques, and advanced sensor fusion methods while considering various localization technologies like computer vision, WiFi, RFID, and Ultra Wideband (UWB). Addressing challenges related to energy efficiency, tracking accuracy, and scalability is crucial for ensuring these systems reliably serve diverse applications, including augmented reality and robotics, in ever-changing indoor settings [19, 8]. By tackling these challenges, future research can contribute to developing resilient and versatile indoor localization solutions capable of meeting the demands of complex and dynamic environments.

9 Conclusion

Indoor localization technologies are pivotal in revolutionizing operational dynamics and enhancing user experiences across multiple domains. The survey underscores the significant advancements achieved through integrating diverse methodologies, such as the BP neural network with Ultra-Wideband systems, which have substantially increased location accuracy. This progress signals a promising trajectory for future research and development. The potential of federated learning is exemplified by the FedLoc-AC framework, which enhances localization accuracy in heterogeneous settings, showcasing the adaptability of machine learning techniques in this field.

The application of machine learning models, like the random forest, demonstrates remarkable accuracy, highlighting their practical utility and potential for further innovation. The implementation of Local Differential Privacy frameworks ensures robust data protection while maintaining accuracy, addressing privacy concerns effectively. In healthcare, the deployment of digital biomarkers for cognitive ability prediction exemplifies the expanding role of these technologies in medical contexts, emphasizing their transformative impact.

Innovative approaches to identifying and navigating surprising regions within indoor environments have further refined user navigation capabilities. As these technologies advance, their ability to offer precise, efficient, and flexible solutions will continue to meet the evolving demands of modern indoor spaces. The survey reflects a trend toward integrating cutting-edge methodologies to overcome current challenges, positioning indoor localization technologies as essential tools for achieving greater precision and flexibility across various sectors.

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References

- [1] Shixiong Xia, Yi Liu, Guan Yuan, Mingjun Zhu, and Zhaohui Wang. Indoor fingerprint positioning based on wi-fi: An overview. *ISPRS international journal of geo-information*, 6(5):135, 2017.
- [2] Muhammad A. Shah, Bhiksha Raj, and Khaled A. Harras. Inferring room semantics using acoustic monitoring, 2017.
- [3] Angela Botros, Narayan Schütz, Christina Röcke, Robert Weibel, Mike Martin, René Muri, and Tobias Nef. Eigenbehaviour as an indicator of cognitive abilities, 2021.
- [4] Hojjat Navidan, Vahideh Moghtadaiee, Niki Nazaran, and Mina Alishahi. Hide me behind the noise: Local differential privacy for indoor location privacy, 2022.
- [5] Aurora Polo-Rodriguez and Javier Medina-Quero. Discriminating sensor activation in activity recognition within multi-occupancy environments based on nearby interaction, 2022.
- [6] Rajdeep Kumar Nath and Himanshu Thapliyal. Wearable health monitoring system for older adults in a smart home environment, 2021.
- [7] Gergely Biczok, Santiago Diez Martinez, Thomas Jelle, and John Krogstie. Navigating mazemap: indoor human mobility, spatio-logical ties and future potential, 2014.
- [8] Faheem Zafari, Athanasios Gkelias, and Kin K Leung. A survey of indoor localization systems and technologies. *IEEE Communications Surveys & Tutorials*, 21(3):2568–2599, 2019.
- [9] Mikkel Baun Kjærgaard. Indoor positioning with radio location fingerprinting, 2010.
- [10] Xin Cheng, Chuan Ma, Jun Li, Haiwei Song, Feng Shu, and Jiangzhou Wang. Federated learning-based localization with heterogeneous fingerprint database, 2022.
- [11] Jayakanth Kunhoth, AbdelGhani Karkar, Somaya Al-Maadeed, and Abdulla Al-Ali. Indoor positioning and wayfinding systems: a survey. *Human-centric Computing and Information Sciences*, 10:1–41, 2020.
- [12] Fakhrul Alam, Nathaniel Faulkner, and Baden Parr. Device-free localization: A review of non-rf techniques for unobtrusive indoor positioning. *IEEE Internet of Things Journal*, 8(6):4228–4249, 2020.
- [13] Charith Perera, Saeed Aghaee, Ramsey Faragher, Robert Harle, and Alan Blackwell. A contextual investigation of location in the home using bluetooth low energy beacons, 2017.
- [14] Vishal Choudhary, Shashi Kant Gupta, Shaohui Foong, and Hock Beng Lim. Distance measurement for uavs in deep hazardous tunnels, 2024.
- [15] Nirmalya Thakur and Chia Y. Han. A simplistic and cost-effective design for real-world development of an ambient assisted living system for fall detection and indoor localization: Proof of concept, 2022.
- [16] Md. Tareq Mahmood and Mohammed Eunus Ali. Learning indoor layouts from simple point-clouds, 2021.
- [17] A survey of indoor localization.
- [18] Saideep Tiku, Danish Gufran, and Sudeep Pasricha. Multi-head attention neural network for smartphone invariant indoor localization, 2022.
- [19] A comprehensive survey of indoor.
- [20] Sunmin Lee, Jinah Kim, and Nammee Moon. Random forest and wifi fingerprint-based indoor location recognition system using smart watch. *Human-centric computing and information sciences*, 9:1–14, 2019.
- [21] Heba Aly and Moustafa Youssef. An analysis of device-free and device-based wifi-localization systems, 2015.

-
- [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, 2022.
 - [23] Smartphone-based cooperative ind.
 - [24] Muhammad Shalihan, Ran Liu, and Chau Yuen. Nlos ranging mitigation with neural network model for uwb localization, 2022.
 - [25] Elsheimy and li satell navig.
 - [26] Antonio Bracco, Federico Grunwald, Agustin Navceovich, Germán Capdehourat, and Federico Larroca. Museum accessibility through wi-fi indoor positioning, 2020.
 - [27] I Santos-González, A Rivero-García, and P Caballero-Gil. Secure indoor location for airport environments, 2022.
 - [28] Ioannis Nasios, Konstantinos Vogklis, Avleen Malhi, Anastasia Vayona, Panos Chatziadam, and Vasilis Katos. Citizen participation: crowd-sensed sustainable indoor location services, 2023.
 - [29] Zhangzhi Zhao, Zhengying Lou, Ruibo Wang, Qingyao Li, and Xing Xu. I-wknn: Fast-speed and high-accuracy wifi positioning for intelligent stadiums, 2021.
 - [30] Mohammadamin Atashi, Mohammad Salimibeni, and Arash Mohammadi. Online dynamic window (odw) assisted two-stage lstm frameworks for indoor localization, 2021.
 - [31] Yanzan Sun, Qinggang Xie, Guangjin Pan, Shunqing Zhang, and Shugong Xu. A novel gen based indoor localization system with multiple access points, 2021.
 - [32] Luan Chen, Iness Ahriz, and Didier Le Ruyet. Aoa-aware probabilistic indoor location fingerprinting using channel state information. *IEEE internet of things journal*, 7(11):10868–10883, 2020.
 - [33] Vahideh Moghtadaiee, Mina Alishahi, and Milad Rabiei. Differentially private gans for generating synthetic indoor location data, 2024.
 - [34] Da Li, Yingke Lei, Xin Li, and Haichuan Zhang. Deep learning for fingerprint localization in indoor and outdoor environments. *ISPRS International Journal of Geo-Information*, 9(4):267, 2020.
 - [35] Haobo Zhang, Jingzhi Hu, Hongliang Zhang, Boya Di, Kaigui Bian, Zhu Han, and Lingyang Song. Metaradar: Indoor localization by reconfigurable metamaterials, 2023.
 - [36] Erick Schmidt and David Akopian. Indoor positioning system using wlan channel estimates as fingerprints for mobile devices, 2019.
 - [37] Indoor localization by f using.
 - [38] Amir Fathalizadeh, Vahideh Moghtadaiee, and Mina Alishahi. Indoor location fingerprinting privacy: A comprehensive survey, 2024.
 - [39] Artyom Nikitin, Christos Laoudias, Georgios Chatzimilioudis, Panagiotis Karras, and Demetrios Zeinalipour-Yazti. Indoor localization accuracy estimation from fingerprint data. In *2017 18th IEEE International Conference on Mobile Data Management (MDM)*, pages 196–205. IEEE, 2017.
 - [40] Zaafer Barahim, M. Razvi Doomun, and Nazrana Joomun. Low-cost bluetooth mobile positioning for location-based application, 2012.
 - [41] A review of indoor localization.
 - [42] Faheem Zafari, Athanasios Gkelias, and Kin Leung. A survey of indoor localization systems and technologies, 2019.
 - [43] Eric S. Ferraz and Celso B. Carvalho. Localizacao 3d em sistemas rfid com leitor movel, 2017.

-
- [44] Paula Fraga-Lamas, Diego Noceda-Davila, Tiago M. Fernández-Caramés, Manuel A. Díaz-Bouza, and Miguel Vilar-Montesinos. Smart pipe system for a shipyard 4.0, 2024.
- [45] Sebastian Feld, Andreas Sedlmeier, Markus Friedrich, Jan Franz, and Lenz Belzner. Bayesian surprise in indoor environments, 2020.
- [46] Zhaoguang Yi, Xiangyu Wen, Qiyue Xia, Peize Li, Francisco Zampella, Firas Alsehly, and Chris Xiaoxuan Lu. Multimodal indoor localization using crowdsourced radio maps, 2024.
- [47] Milutin Pajovic, Pu Wang, Toshiaki Koike-Akino, Haijian Sun, and Philip V Orlik. Fingerprinting-based indoor localization with commercial mmwave wifi-part i: Rss and beam indices. In *2019 IEEE Global Communications Conference (GLOBECOM)*, pages 1–6. IEEE, 2019.
- [48] Chenyu Wang and Zihuai Lin. Precise indoor positioning based on uwb and deep learning, 2022.
- [49] Amin Kargar-Barzi, Ebrahim Farahmand, Nooshin Taheri Chatrudi, Ali Mahani, and Muhammad Shafique. An edge-based wifi fingerprinting indoor localization using convolutional neural network and convolutional auto-encoder, 2024.
- [50] Journal of location based servic.
- [51] Stefan Ruehrup. On the use of gnss for automatic detection of attenuating environments, 2020.
- [52] Vamsi Karthik Vadlamani, Manish Bhattarai, Meenu Ajith, and Manel Martinez-Ramon. A novel indoor positioning system for unprepared firefighting scenarios, 2020.
- [53] Kevin M. Chen and Ronald Y. Chang. Semi-supervised learning with gans for device-free fingerprinting indoor localization, 2020.
- [54] Caifa Zhou and Yang Gu. Joint positioning and radio map generation based on stochastic variational bayesian inference for fwips, 2017.
- [55] Indoor fingerprint positioning b.
- [56] William Falcon and Henning Schulzrinne. Predicting floor-level for 911 calls with neural networks and smartphone sensor data, 2018.
- [57] Tiantian Liu, Huan Li, Hua Lu, Muhammad Aamir Cheema, and Lidan Shou. An experimental analysis of indoor spatial queries: Modeling, indexing, and processing, 2020.
- [58] Kyeong Soo Kim, Sanghyuk Lee, and Kaizhu Huang. A scalable deep neural network architecture for multi-building and multi-floor indoor localization based on wi-fi fingerprinting. *Big Data Analytics*, 3:1–17, 2018.
- [59] Fahed Awad, Aisha Al-Sadi, Fida’a Al-Quran, and Abdulsalam Alsmady. Distributed and adaptive location identification system for mobile devices, 2018.
- [60] Moustafa Elhamshary, Anas Basalamah, and Moustafa Youssef. A fine-grained indoor location-based social network, 2016.
- [61] Scott A. Carter, Daniel Avrahami, and Nami Tokunaga. Using inaudible audio to improve indoor-localization- and proximity-aware intelligent applications, 2020.
- [62] Chenglong Li, Sibren De Bast, Emmeric Tanghe, Sofie Pollin, and Wout Joseph. Towards fine-grained indoor localization based on massive mimo-ofdm system: Experiment and analysis, 2021.
- [63] Shilong Dai, Liang He, and Xuebo Zhang. Autonomous wifi fingerprinting for indoor localization. In *2020 ACM/IEEE 11th International Conference on Cyber-Physical Systems (ICCPs)*, pages 141–150. IEEE, 2020.
- [64] Marcin Uradzinski, Hang Guo, Xiaokang Liu, and Min Yu. Advanced indoor positioning using zigbee wireless technology. *Wireless Personal Communications*, 97:6509–6518, 2017.

-
- [65] Zhiping Jiang, Jizhong Zhao, Xiang-Yang Li, Wei Xi, Kun Zhao, Shaojie Tang, and Jinsong Han. Communicating is crowdsourcing: Wi-fi indoor localization with csi-based speed estimation, 2013.
- [66] Yu Zhang and Xiao-Yang Liu. A tensor completion approach for efficient and robust fingerprint-based indoor localization, 2017.

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