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Indoor Positioning Systems: Technologies and Selection Strategies

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***Abstract*— Indoor Positioning Systems (IPS) have emerged as essential technologies for achieving accurate localization and navigation within enclosed environments where satellite-based systems, such as the Global Navigation Satellite System (GNSS), are unreliable. This article provides a comprehensive overview of the major IPS technologies, highlighting their operating principles, advantages, and limitations. The study examines a diverse range of positioning methods, including computer vision-based systems with dynamic tracking capabilities, pedestrian dead reckoning (PDR) solutions that function independently of external infrastructure, and communication signal–based approaches such as Ultra-Wideband (UWB), Radio Frequency Identification (RFID), Bluetooth Low Energy (BLE), Wi-Fi, and ZigBee. Each technology demonstrates distinct performance characteristics in terms of accuracy, cost efficiency, scalability, and energy consumption. By systematically comparing these approaches, this work identifies the contexts in which each technology performs optimally and discusses the trade-offs associated with their implementation. Furthermore, the paper synthesizes recent advancements that integrate artificial intelligence, machine learning, and sensor fusion techniques to enhance positioning precision and robustness under complex indoor conditions. The findings of this review aim to assist researchers, engineers, and practitioners in selecting the most appropriate IPS solution for specific application domains, facilitating informed decision-making in designing effective and reliable indoor localization systems.**

***Keywords*—Indoor Positioning Systems; UWB, RFID, Computer Vision; BLE, WiFi, ZigBee, PDR**

I. INTRODUCTION

Positioning systems are one of the most useful technologies that has been developed. The usage of this technology varies from the military field to hospitality, search and rescue, and even recreation field. Global Navigation Satellite Systems (GNSS) are one of the most popular positioning or navigation systems. As the name suggest, GNSS is a satellite-based positioning system. Global Positioning System (GPS), which people uses to assist the process of navigating them from a place to another is a type of GNSS. However, GNSS signals are disturbed and not really reliable to be used indoor [1]. This inherent limitation of GPS has long spurred the quest for alternative solutions. Researchers have tirelessly tackled the challenge of indoor positioning, recognizing its immense potential. The rise of smartphones and smartwatches, carried by most people like digital appendages, has only intensified this pursuit. These ubiquitous devices hold the key to unlocking the doors of indoor location awareness.

GPS's intrinsic restriction has long fuelled the search for alternate alternatives. Indoor positioning system (IPS) is designed to enable precise location tracking and navigation within enclosed spaces. Researchers have worked extensively on the problem of indoor placement, seeing its enormous potential. The emergence of smartphones and smartwatches, which most people carry about like digital appendages, has only fuelled this drive. IPS can be used in various applications. Humans are finding specific uses at train stations, bus terminals, retail malls, museums, airports, and libraries. Indoor navigation devices benefit visually challenged persons as well. Unlike outdoor areas, navigation through indoor areas are more difficult. Indoor environments are typically densely packed with obstacles that impede signals between emitters and receivers, and a diverse range of materials, forms, and sizes have a greater impact on signal transmission than in outside conditions [2].

These commonplace technologies hold the key to opening the doors to indoor location awareness. This study conducts an examination of the developing topic of indoor positioning devices. We reveal a patchwork of techniques, each contending for supremacy in this new environment. From computer vision's keen eye for landmark recognition [3] to the pin-point accuracy of Ultra-Wideband (UWB) [4] radar, from Wi-Fi [5] and Bluetooth's [6] ubiquitous radio waves to the niche communication protocols of RFID [7] and ZigBee [8], and even the stride-counting ingenuity of Pedestrian Dead Reckoning (PDR) [9], each technology has distinct strengths and limitations. The purpose of this survey is to review the various technologies that have been employed for IPS.

The rest of the paper is organized as follows: Section II addresses the previous works of surveying the trend of IPS. This includes the type of IPS technologies and techniques. Next, Section III describes the three types of IPS technologies. The improvements of the IPS or the current findings are discussed in Section IV. Finally, the conclusions are drawn in Section V.

II. RELATED WORKS

From time to time, researchers and inventors have come out with various technologies to be used as a part of the IPS. Improvements are made actively to increase and improve the performance of the IPS depending on the situation and scenarios that we have been facing. Recent studies have sought to organize the diverse landscape of indoor positioning system (IPS) technologies by classifying them according to their underlying principles and technical features. In particular, Mendoza-Silva et al. [10] provided a comprehensive meta-review that grouped IPS methods based on sensing techniques and implementation characteristics, while Brena et al. [2] traced the evolution of these technologies from early signal-based approaches to more advanced hybrid systems. Collectively, these works establish a systematic understanding of IPS development and highlight how varying methodological foundations shape the performance and applicability of different positioning solutions. Brena et al. [2] classified IPS technologies into 5 main groups which are optical technologies, sound-based technologies, radio frequency technologies, passive/ without embedded information technologies, and hybrid technologies. For more specific technologies and to which classification they are categorized, table 1 can be referred. These classifications are based on the type of signal used, whether the signal is received and analyzed, and whether or not the signal contains intentionally embedded pattern of symbolic information [2]. However, authors of [10] took a more general approach by classifying not putting the classification based on the 3 criteria stated in [2]. The commonly used IPS technologies stated by the authors are grouped into 10 which are light, computer vision, sound, magnetic fields, dead reckoning, UWB, Wi-Fi, BLE, Radio Frequency Identification (RFID) and Near Field Communication (NFC), and other technologies. The surveys presented in [2] and [10] offer a comprehensive overview of the indoor positioning systems (IPS) domain, outlining many of the technologies currently in widespread use. However, while both studies provide valuable breadth, they do not examine each technology in substantial technical depth.

Zafari et al. [11] provided a detailed survey identifying eight major indoor positioning system (IPS) technologies, most of which are based on communication signals. The study discusses Wi-Fi, Bluetooth Low Energy (BLE), ZigBee, RFID, ultra-wideband (UWB), acoustic signals, ultrasound, and visible light, offering concise explanations of their underlying working principles and summarizing key research findings associated with each. Lastly, Kunhoth et al. mentioned in [12] 7 IPS technologies which are computer vision, Wi-Fi, BLE, RFID, VLC, UWB and PDR. Although they only addressed 7 IPS technologies, these 7 are the most common technologies used in IPS nowadays because of each of their advantages such as low cost, easy to be accessed and used, etc. These 7 IPS technologies are also discussed in detail on their history, mechanism, recent developments, and future improvements. Overall, each of the previous works has their own strengths. Table 1 shows the summary of the previous works and the IPS technologies mentioned in the articles.

Depending on what type of IPS technology is used in the system, the positioning techniques can be different too. Even the same IPS technology can have multiple way of positioning techniques that can be used. We distinguish between techniques and technologies, where "technique" refers to some basic abstract tool that is not necessarily tied to physical media and could be used in several "technologies"; "technologies" are specific ways of using physical signals registered through sensors, such as radio waves or magnetic fields, to achieve the goals of an IPS. According to Brena et al. [2], the process of location estimation in indoor positioning systems can be conceptually divided into three distinct stages. The first step is evident, in which instruments engaged measure signal properties. The second stage is range estimation, in which devices utilise the measurements or evidence collected to estimate the distance to/from the item to be located. The next stage involves combining such range estimations to estimate position. Brena et al. described the techniques of positioning used in the IPS in detail and includes as many techniques as possible in [2].

Both Mendoza-Silva et al. [10] and Kunhoth et al. [12] focused on classifying indoor positioning techniques into four principal categories: time-of-arrival (ToA), also referred to as time-of-flight (ToF) in some studies; time-difference-of-arrival (TDoA); angle-of-arrival (AoA); and received signal strength (RSS) or received signal strength indicator (RSSI).

Table I. Different Indoor Positioning Technologies reported in previous works.

Literature	Ips Technologies Mentioned
Brena et al. [2]	1. Optical Technologies: Infrared, VLC 2. Sound-Based Technologies: Ultrasound, Audible Sound 3. Radio Frequency Technologies: Wi-Fi, BLE, ZigBee, RFID, UWB 4. Passive/ without Embedded Information Technologies: Magnetic Field, Inertial Technology, Passive Sound-Based Technology, Passive Visible Light, Computer Vision 5. Hybrid Technologies
Mendoza-Silva et al. [10]	1. Light: VLC, Infrared 2. Computer Vision 3. Sound: Audible Sound, Ultrasound 4. Magnetic Fields 5. Dead Reckoning: PDR 6. UWB 7. Wi-Fi 8. BLE 9. RFID and NFC 10. Other Technologies: Cellular Networks, Wireless Sensor Network
Zafari et al. [11]	1. Wi-Fi 2. BLE 3. ZigBee 4. RFID 5. UWB 6. Visible Light 7. Acoustic Signal 8. Ultrasound
Kunhoth et al. [12]	1. Computer Vision 2. RFID 3. Wi-Fi 4. VLC 5. UWB 6. BLE 7. PDR

These classifications capture the most prevalent measurement principles employed across a wide range of IPS technologies. On the other hand, Zafari et al. [11] provides the most comprehensive and in-depth analysis among the recent studies, offering detailed explanations of the underlying principles and comparative evaluations of various indoor positioning technologies. Each detection technique discussed in [11] is presented with thorough detail, supported by the inclusion of relevant equations and clear illustrative diagrams that enhance conceptual understanding. It is suggested to refer to the article for clearer understanding regarding the location detection techniques used in IPS. Table 2 shows the summary of detection techniques addressed in the previous works.

III. TYPES OF INDOOR POSITIONING SYSTEMS

IPS can be classified into 3 categories, based on the adopted positioning technologies [12]. Computer vision, communication technology, and pedestrian dead reckoning (PDR).

A. Computer Vision

Computer vision IPS takes advantage of the pervasiveness of visual clues within buildings to turn seemingly static settings into rich data landscapes [13]. Cameras strategically placed across the environment capture the environment, methodically analysing pixelated landscape for identifying landmarks, architectural details, or signs. The collected frames are then compared to a pre-existing computer model, locating the user's position with astonishing precision [3]. This dependence on underlying environmental properties provides inherent benefits such as broad application, scalability, and possibly unsurpassed accuracy. However, for best performance, proper calibration and illumination are required, and complicated settings with dynamic changes or occlusions can provide considerable obstacles [11].

B. Communication Technology

To determine user position, communication technologies IPS rely on existing infrastructures like as Wi-Fi, Bluetooth, and even ultrasonic signals. Sensors strategically positioned around the building collect and analyse the strength and timing of these signals sent by user devices, constructing a tapestry of data that indicates to their location within the building [12]. This strategy thrives on convenience: by using existing infrastructure, no extra installations are required, and its ubiquitous availability makes it easily deployable in a variety of scenarios [14]. However, it is subject to signal interference, complicated layouts, and multi-story structures, which can reduce its accuracy. Furthermore, depending merely on signal strength may not deliver the pinpoint precision required for applications requiring centimetre-level precision. In this article, we will be discussing on the usage of UWB, RFID, Wi-Fi, Bluetooth, and ZigBee in IPS.

C. PDR

Pedestrian dead reckoning IPS venture into self-contained positioning, freeing users from reliance on external signals or infrastructure. These systems measure movement within the building by utilising sensors such as accelerometers and gyroscopes installed in user devices. Each step, turn, and tilt adds to a virtual map of the user's journey, meticulously built by their own actions [15]. This independence has intrinsic benefits, such as continual positioning even in situations with little infrastructure or signal coverage. However, PDR is prone to drift over time. Accumulated errors caused by sensor limits or ambient conditions might bias location estimations over time [16], necessitating frequent calibration or integration with other IPS approaches for best accuracy.

Table II. Different Indoor Positioning location detection techniques reported in previous works.

Literature	Ips Technologies Mentioned
Brena et al. [2]	1. Multilateration 2. ToA/ ToF 3. TDoA 4. AoA 5. RSS 6. Proximity 7. Fingerprinting 8. Signal Propagation 9. Multipath Environment 10. Line of Sight (LoS) 11. Synchronization
Mendoza-Silva et al. [10]	1. ToA 2. TDoA 3. AoA 4. RSS
Zafari et al. [11]	1. RSSI 2. Channel State Information (CSI) 3. Fingerprinting/ Scene Analysis 4. AoA 5. ToF/ ToA 6. TDoA 7. Return ToF (RToF) 8. Phase-of-Arrival (PoA)
Kunhoth et al. [12]	1. ToA 2. TDoA 3. AoA 4. RSS

IV. CURRENT TECHNOLOGIES

A. Computer Vision

The application of computer vision algorithms to pictures captured using imaging techniques such as cameras is referred to as computer vision localization. The analyses discover important elements in the scene that allow for the estimation of the locations of entities in the scene or the position of the imaging equipment recording the scene [10]. The technology takes real-time video or photos and extracts crucial aspects from the situation, such as unique visual markers or recognisable patterns. The system can precisely compute the location and orientation of objects or persons inside the space by analysing images and comparing them to a pre-existing map or reference database.

Fusco et al. [3] focused on enhancing indoor navigation for individuals with visual impairments by developing a smartphone-based system that integrates sign recognition with visual–inertial odometry (VIO) to enable accurate localization and guidance. This user-friendly approach leverages readily available smartphones and pre-existing maps, empowering individuals with independent mobility despite their visual limitations. Chao et al. [17] explores 3D positioning for mobile robots controlled by tablets, utilizing a single camera and user-selected targets for estimating the target's location. While requiring precise camera calibration and robot movement, this method showcases the potential of computer vision for intuitive robot control.

With the emergence of virtual reality (VR) and augmented reality (AR), Huang et al. [18] proposed a novel AR approach for indoor navigation called Augmented Reality Based Indoor Navigation System (ARBIN). The technology excels at properly putting AR objects on smartphone screens by using BLE beacons for location and route planning. ARBIN delivers exact navigation directions by improving distance prediction between beacons and phones and enhancing 3D model overlay techniques, particularly in huge structures where typical 2D maps fail. This study confirms the system's usefulness through experimental validation, heralding more intuitive and user-friendly indoor navigation experiences.

Li et al. [19] conducted another study on augmented reality (AR)–based indoor navigation, proposing a vision-driven approach that utilizes a 3D feature database for camera localization and precise indoor positioning. It uses RGB-D SLAM (Simultaneous Localization and Mapping) and deep learning technologies to produce a 3D feature database for correct camera pose data. The system also includes an AR registration methodology for incorporating AR experiences into a gaming engine. This adaptive solution, with a remarkable average localization accuracy of 35cm, has potential applications in AR, robotics, indoor mapping, and self-driving automobiles, pushing the frontiers of camera localization for a variety of real-world scenarios.

Computer vision based IPS provide various benefits by interpreting visual data via image processing and pattern recognition. One significant advantage is the ability to give exact location in dynamic conditions when traditional approaches could fail [3]. It can also help with gesture recognition and object identification [12], improving the user experience overall. However, obstacles include lighting sensitivity, potential privacy concerns owing to visual data gathering, and the requirement for significant computer resources.

B. Communication Technologies

1) UWB: Ultra-Wide Band (UWB) technology is used in IPS by estimating the distance between anchors and tags, using time-based ranging algorithms [20]. UWB utilizes short-duration, low-power radio frequency pulses to determine the precise location of objects or devices within an indoor environment. UWB's high precision and resistance to interference make it suitable for applications like asset tracking, indoor navigation, and location-based services in environments where accuracy is crucial.

The study presented in [21] offers a comparative analysis of Wi-Fi and ultra-wideband (UWB) fingerprinting techniques under similar experimental conditions to evaluate their relative positioning performance. While both offer similar accuracy with traditional KNN algorithms, UWB performs better when utilizing a novel dynamic KNN algorithm that leverages channel features. This suggests UWB's potential for more flexible and potentially more accurate indoor positioning systems.

Hao et al. [22] proposes a new UWB indoor positioning method using the OVSF-TH algorithm, spectral density analysis, and triangulation. It's simple, inexpensive, and accurate even in non-line-of-sight environments. The key contributions of [22] include leveraging ultra-wideband (UWB) signals to extract richer positional information and incorporating the analysis of signal “blocking” effects to enhance directional accuracy in indoor positioning.

Ridolfi et al. [23] investigated the use of ultra-wideband (UWB) technology for tracking athletes’ movements, experimentally evaluating its performance in capturing precise sport postures and motion dynamics. It analyzes tag placement and movement patterns' impact on accuracy. Particle and Kalman filters with optimizations are implemented, showing good results with average errors of 20 cm and proves that UWB is suitable for dynamic athletic activities.

With the emergence of machine learning (ML) and artificial intelligence (AI), everyone knows that it can be beneficial to human in various field. Che et al. [20] discusses NLoS effects and existing ML algorithms to mitigate them. ML algorithms such as SVM, DT, and k-NN are shown to be able to help in NLoS environments.

Another improvement was proposed in 2022, which is UWB IPS based on a digital twin [24]. It uses perception-prediction feedback and error mitigation with neural networks to improve accuracy. A case study validates the system with significant accuracy improvement. The key contributions of [24] involve the integration of a digital twin framework into a UWB-based indoor positioning system to optimize anchor placement and mitigate positioning errors.

UWB IPS offer high precision [20] with low latency, enabling accurate location tracking in real-time. UWB's advantage lies in its ability to deliver precise positioning even in challenging environments, such as multipath and dense obstacle scenarios [25, 26]. However, UWB systems may face challenges in terms of higher implementation costs and power consumption.

2) RFID: RFID is the core technology required to realise the Internet of Things (IoT) and cyber-physical systems (CPS), and is widely utilised in health monitors, smart homes, smart cities, vehicle positioning, construction, supply chain management, and item tracking, among other applications [27]. RFID's low cost, long life, low power consumption, and ease of deployment entice numerous researchers to employ it in interior situations. RFID used in indoor positioning is less expensive and uses less energy than ultrasonic, Wi-Fi, and Bluetooth. RFID systems are typically comprised of tags, readers, and a back-end computer system. Most IPS prefer the use of ultra-high-frequency (UHF) RFID technology due to its broader read/write spectrum and increased metadata capabilities for the RFID tags being read [28]. Advanced operations find better support in the higher-frequency bands.

Manman et al. [29] introduces a new method for indoor RFID positioning that combines AP clustering and a refined particle swarm algorithm. The clustering divides the area based on signal strength similarity, reducing the search space for the particle swarm algorithm. This leads to faster and more accurate tag location while minimizing human intervention in cluster selection.

A single-antenna indoor positioning system (IPS) utilizing multiple beams for direction and power control was proposed in [28]. This approach removes the need for multiple physical antennas and enables two-dimensional localization with an extended range and improved accuracy compared to conventional methods. For indoor mobile robot self-localization, Mi Jian et al. [30] developed an HF-band RFID system incorporating multiple scanners and passive tags.

A novel approach for indoor object localization using passive RFID tags deployed in the environment is proposed [7]. Mobile devices receive signals from these tags, allowing their location to be estimated through a developed algorithm. This tag-free method offers flexibility and easy implementation while achieving high accuracy through optimized tag deployment strategies.

In most RFID positioning systems, more than one antenna is required to allow the positioning algorithm to reach greater precision. Furthermore, some researchers have suggested single antenna-based locating systems that are better suited for usage in interior conditions. Then, data mining approaches may be employed to increase the accuracy of indoor localization algorithms, and more sensors can be used for indoor placement [31]. Weng et al. [32] demonstrated a power-adaptation approach that improved location accuracy in a single antenna RFID system.

Finally, the limitations of the LANDMARC algorithm, which relies on easily disrupted Received Signal Strength for positioning [27]. LANDMARC is an algorithm that estimates the location of an RFID tag by comparing its signal strengths to those of reference tags with known locations [33]. Many academics have proposed improvements to the LANDMARC technique in order to improve the accuracy, robustness, and depth of operation while performing localization. A Bayesian Probability and K-Nearest Neighbour (BKNN) method was proposed, which applies a Gaussian filter to reduce noise and interference and determines the most probable location based on neighbouring reference tags [27]. This method significantly reduces location errors compared to traditional methods, showcasing an average error of only 15 cm.

RFID IPS are cost-effective and excel in asset tracking and identification. RFID's main advantage lies in its ability to operate without a direct line of sight and in harsh environmental conditions [27, 28]. However, the range limitation and potential interference from metal objects can pose challenges in certain applications [7].

3) Wi-Fi: Wi-Fi-based IPS use signals from Wi-Fi access points to identify the location of devices within interior settings. This is accomplished through methods like as signal triangulation or trilateration, which involve measuring angles or distances between the device and various known access points [34]. Wi-Fi fingerprinting entails compiling a database of signal strength patterns at numerous places, and real-time comparisons help in determining the location of a device [12]. The Received Signal Strength Indicator (RSSI) is a critical statistic that calculates distances based on the power level received from access points. Machine learning algorithms, crowdsourcing, collaborative positioning, and integration with other sensors contribute to enhancing accuracy and adapting to changing environments.

Ali et al. [35] proposed a self-updating Wi-Fi positioning system that avoids manual calibration. Instead of pre-built radio maps, it learns propagation loss parameters from IoT sensors in real-time, updating maps automatically. While using simple wall information instead of complex maps, it achieves comparable accuracy to traditional survey-based methods.

Ko et al. [36] has successfully implemented a passive fingerprinting system using an active fingerprinting radio map to reduce missing RSSI values. To the best of our knowledge, this is the first study to take optimal placement of Wi-Fi Sniffers into account for Wi-Fi-based passive fingerprinting implementation in the real world in order to reduce positioning errors, which can serve as a baseline for future related research.

Ye and Peng [37] enhanced Wi-Fi fingerprinting accuracy for robotic navigation by employing denser reference points, standardized signal strength values, and an adaptive K-Nearest Neighbour (KNN) algorithm to minimize localization errors. When integrated with a grid-based navigation framework, their approach achieved a 62% navigation success rate within 0.8 meters, demonstrating significant improvements in positioning precision and reliability. Zhang et al. [38] proposed an answer to the challenge of limited channel state information (CSI) in Wi-Fi positioning. It proposes collecting CSI along pre-determined trajectories instead of at individual stationary points, capturing continuous spatial and temporal information. This data is then processed by a deep learning network, significantly outperforming conventional methods based on stationary CSI.

Chan et al. [39] developed a passive Wi-Fi–based indoor positioning system that eliminates the need for user interaction or device modification. Their approach employs a genetic algorithm to optimize the spatial placement of Wi-Fi sniffers, maximizing localization accuracy by analyzing signal strength data from nearby devices. This proof-of-concept demonstrates the feasibility of achieving real-time passive indoor positioning, highlighting its potential for unobtrusive and scalable deployment in practical environments. Wi-Fi-based IPS utilize existing infrastructure for location tracking, offering widespread coverage. Wi-Fi's advantage lies in its availability and compatibility with a variety of devices. However, accuracy may vary, especially in crowded areas [35], and the reliance on existing Wi-Fi networks may limit its precision [2].

4) Bluetooth: Bluetooth technology has been primarily developed for short-range wireless transmission with low power consumption and low cost [40]. Then, with the publication of the Bluetooth 4.0 specification in 2010 [40], Bluetooth Low Energy (BLE) emerged as an appealing wireless technology that may be used in indoor location systems. BLE has now been used for a variety of location-based services, ranging from proximity detection to positioning in real-time location systems (RTLS) [41]. Furthermore, BLE technology is widely available on practically all portable devices, including smartphones and electrical development kits [11].

The study of Maneerat and Kaemarungsi [42] focuses on optimizing the design of BLE-based IPS for better accuracy and cost efficiency. It analyzes three different designs (proximity, trilateration, and scene analysis) across two building sizes. The findings suggest that the proximity is least accurate (5-7m error) and suitable for low-cost applications, the trilateration offers good accuracy (3-5m) with efficient reference node deployment (can reduce nodes by 154% vs. scene analysis), and the scene analysis provides the best scalability for high accuracy (≤3m) but requires more nodes (still 40% less than proximity). Thus, framework helps system designers choose the optimal design based on desired accuracy and cost constraints.

Rozum et al. [43] proposed a simplified Bluetooth Low Energy (BLE)–based indoor positioning system designed for efficient deployment in narrow corridors. The system employs the Log-Distance Path Loss (LDPL) model within a one-dimensional framework, where the perpendicular coordinate is considered negligible, and incorporates a wireless Single Input Multiple Output (SIMO) configuration to mitigate RSSI fluctuations and enhance portability. Experimental results demonstrate an average positioning accuracy of 0.92 meters without the need for filtering algorithms, indicating its suitability for corridor-based localization with minimal implementation complexity.

Sthapit et al. [44] proposes a BLE-based IPS that utilizes machine learning for fingerprinting. This approach avoids the time-consuming manual fingerprinting process. The system achieved an average estimation error of 50 cm, demonstrating the potential of machine learning for improving BLE-based indoor positioning accuracy.

Lastly, Bai et al. [45] presented in their research, a low-cost BLE system for monitoring user location in home environments. It uses a BLE beacon worn by the user and strategically placed Raspberry Pis with BLE antennas. The system employs both trilateration and fingerprinting to determine user location and track their living patterns. The results show that the system can accurately track user location within the home, even with variations in beacon positions and quality. This opens up possibilities for monitoring user health and activity patterns in a non-intrusive manner.

End users now have simple access to many critical capabilities of IPSs, such as navigation and tracking services, because to the broad deployment of BLE technologies such as Bluetooth beacons. Thus, the current study uses BLE technology and a new installation design technique to evaluate how the systematic design of an IPS might be used to accomplish a needed performance target for various indoor location-based applications. BLE Indoor Positioning Systems leverage the ubiquity of BLE-enabled devices and offer energy efficiency. BLE's advantage is its compatibility with smartphones and other consumer devices [16], making it widely accessible. Nonetheless, limited range and potential signal obstructions can impact accuracy in complex indoor environments.

5) ZigBee: ZigBee is a Bluetooth-like technology, which runs at around a fourth of Bluetooth's maximum transmission throughput of 1 Mbps [46]. The low data rate makes it unsuitable for high-speed data transmission applications, but the approach allows for multiyear battery life and connectivity to a large number of nodes. Because of its unique features, ZigBee is the best choice for implementing an ad hoc, on-demand, low-cost, and low-power location tracking, and monitoring system. Zigbee supports a huge number of nodes, around 65000 nodes. The replacement of a battery in a WSN (wireless sensor networks) is a critical task. Zigbee has a very long battery life, thus battery replacement is not an issue. For position estimate, the location fingerprinting approach is applied [8].

Athira et al. [8] introduced a low-cost ZigBee-based system for indoor location tracking uses "fingerprinting" to locate people or objects, a system of sensors collecting signal strengths from access points, creating a database of "fingerprints" for different locations. When a location is requested, the system compares current signal strengths to the database and returns the best match. This provides a simple and effective indoor positioning solution.

Loganathan et al. [46] improved indoor localization accuracy by fusing ZigBee signal strength (RSSI) and odometry data. A novel framework optimizes weighting between these methods based on their individual limitations. A self-adaptive filter further adjusts weights during movement, leading to a more efficient and accurate localization scheme. This approach significantly improves location tracking compared to existing methods.

6) Shen et al. [47] introduced a ZigBee-based sensor network that estimates distances between nodes and reference points using received signal strength indicator (RSSI) measurements. By applying both average and Gaussian filtering models, the system achieves rapid location estimation with moderate accuracy. This straightforward and hardware-independent approach provides a practical solution for fundamental indoor positioning applications.

Cheng and Syu [48] applied a backpropagation neural network (BPNN) to an area-based ZigBee positioning system to enhance localization accuracy. By learning the signal characteristics of the surrounding environment, the BPNN model provides more precise location estimates than traditional nearest neighbour algorithms. This study highlights the potential of neural network–based approaches to improve ZigBee indoor positioning performance, even under challenging conditions such as signal interference and multipath effects.

ZigBee Indoor Positioning Systems, based on low-power, low-data-rate wireless communication, are energy-efficient and suitable for applications with numerous nodes [8]. ZigBee's advantage lies in its ability to create robust mesh networks. However, its limited data transfer rates may restrict its use in certain high-throughput scenarios, and interference from other ZigBee networks can affect performance.

C. Pedestrian Dead Reckoning

The primary idea is to tally up minor movements from a known starting location to predict the pedestrian's trajectory. PDR's main issue is the substantial error propagation caused by relative movement changes. After a few steps, the changes in step length and direction add up to produce highly imprecise position detection. Therefore, a recalibration of the user position is required at regular intervals [16, 15]. As detailed by Han et al [9], PDR is a frequently used localization approach that employs an Inertial Measurement Unit module or portable devices such as smartphones [16]. To minimize the drift of PDR, it must be combined with other signals such as GPS [14], Wi-Fi [49, 50], BLE [51], and so on, as PDR alone is prone to drift.

The application of computer vision algorithms to pictures captured using imaging techniques such as cameras is referred to as computer vision localization. The analyses discover important elements in the scene that allow for the estimation of the locations of entities in the scene or the position of the imaging equipment recording the scene [10]. The technology takes real-time video or photos and extracts crucial aspects from the situation, such as unique visual markers or recognisable patterns. The system can precisely compute the location and orientation of objects or persons inside the space by analysing images and comparing them to a pre-existing map or reference database.

Lu et al. [52] explores a novel way to use inertial measurement units (IMUs) for indoor navigation by placing them on the chest instead of the traditional location of the hips. This allows for more accurate step length estimation and avoids the limitation of zero-velocity updates due to upper body movement. Additionally, the system incorporates map-matching with particle filtering and altitude tracking using a barometer for 3D positioning in multi-floor buildings. This approach achieved a mean error of 5.2 meters after an 800-meter walk.

Zhu et al. [53] proposed a multi-source indoor positioning framework that integrates Wi-Fi, Bluetooth, and pedestrian dead reckoning (PDR) through an improved weighted centroid algorithm combined with adaptive constraint fusion techniques. This hybrid approach effectively mitigates Wi-Fi signal instability and the cumulative drift errors inherent in PDR, achieving higher localization accuracy and stability than any single-technology method. Experimental results confirm that the fusion-based system consistently outperforms standalone positioning techniques in both precision and robustness.

In 2021, Lee et al. [54] introduces a Kalman filter-based fusion of UWB positioning and PDR for accurate indoor localization. UWB's high precision is combined with PDR's continuous tracking capability to compensate for UWB's NLoS errors [55] and PDR's cumulative drift. The proposed scheme utilizes deep learning for speed estimation in PDR and calibrates heading with UWB assistance. The combined approach demonstrates superior performance compared to UWB or PDR alone.

Finally, Han et al. [9] proposes a probabilistic position selection algorithm (PPSA) for indoor localization using RSSI and PDR data. To address the challenges of mixed LoS and NLOS environments, the algorithm incorporates a low-complexity NLoS identification method. This helps mitigate the negative impact of NLoS conditions on RSSI-based localization, leading to improved accuracy and reliability.

PDR Indoor Positioning Systems provide particular benefits since they work independently of terrestrial or satellite cooperating stations, making them self-contained and adaptable to a variety of situations [10, 11]. Furthermore, PDR systems are energy efficient since their transmitter power needs are low in comparison to other positioning methods. Nonetheless, one significant disadvantage of PDR is the cumulative nature of its inaccuracies [16, 52]. Inaccuracies in the estimating process compound over time, resulting in a progressive development of the positional inaccuracy. To address this issue, frequent calibration and integration with supporting technologies are required to assure long-term accuracy in indoor location [16].

V. CONCLUSION

The study discussed the key technologies that are currently used to enable indoor positioning systems, briefly describing the approaches and procedures used in each of them. Each technology's description is backed by connections to other surveys, allowing the reader to utilise this article as a collection of links to more specialised studies. We classified current systems based on the positioning technology used. In the last ten years, we gave a complete evaluation of the different suggested indoor positioning technologies.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest regarding the publication of this paper.

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REFERENCES

[1] A. Nessa, B. Adhikari, F. Hussain and X. N. Fernando, "A Survey of Machine Learning for Indoor Positioning," IEEE Access, vol. 8, pp. 214945-214965, 2020.

[2] R. F. Brena, J. P. García-Vázquez, C. E. Galván-Tejada, D. Muñoz-Rodriguez, C. Vargas-Rosales and J. J. Fangmeyer, "Evolution of Indoor Positioning Technologies: A Survey," Journal of Sensors, vol. 2017, 2017.

[3] G. Fusco and J. M. Coughlan, "Indoor Localization using Computer Vision and Visual-Inertial," Lecture Notes in Computer Science(), vol. 10897, 2018.

[4] F. Mazhar, M. G. Khan and B. Sallberg, "Precise Indoor Positioning Using UWB: A Review of Methods, Algorithms and Implementations," Algorithms and Implementations. Wireless Pers Commun, vol. 97, pp. 4467-4491, 2017.

[5] F. Wang, J. Feng, Y. Zhao, X. Zhang, S. Zhang and J. Han, "Joint Activity Recognition and Indoor Localization With WiFi Fingerprints," IEEE Access, vol. 7, pp. 80058-80068, 2019.

[6] R. Faragher and R. Hale, "Location Fingerprinting With Bluetooth Low Energy Beacons," EEE Journal on Selected Areas in Communications, vol. 33, no. 11, pp. 2418-2428, 2015.

[7] A. Diallo, Z. Lu and X. Zhao, "Wireless Indoor Localization Using Passive RFID Tags," Procedia Computer Science, vol. 155, pp. 210-217, 2019.

[8] K. R. Athira and A. Babu, "Zigbee based Indoor Location Tracking and Monitoring System," International Journal of Recent Technology and Engineering (IJRTE), vol. 7, no. 6, 2-19.

[9] K. Han, H. Xing, Z. Deng and Y. Du, "A RSSI/PDR-Based Probabilistic Position Selection Algorithm with NLOS Identification for Indoor Localisation," ISPRS International Journal of Geo-Information, vol. 7, no. 6, 2018.

[10] G. M. Mendoza-Silva, J. Torres-Sospedra and J. Huerta, "A Meta-Review of Indoor Positioning Systems," Sensors, vol. 19, no. 20, 2019.

[11] F. Zafari, A. Gkelias and K. K. Leung, "A Survey of Indoor Localization Systems and Technologies," IEEE Communications Surveys & Tutorials, vol. 21, no. 3, pp. 2568-2599, 2019.

[12] J. Kunhoth, A. Karkar, S. Al-Maadeed and A. K. Al-Ali, "Indoor positioning and wayfnding systems: a survey," Human-centric Computing and Information Science, vol. 10, no. 18, 2020.

[13] A. Rituerto, G. Fusco and J. M. Coughan, "Towards a Sign-Based Indoor Navigation System for People with Visual Impairments," ASSETS. Annual ACM Conference on Assistive Technologies,, pp. 287-288, 2016.

[14] X. Li, D. Wei, Q. Lai, Y. Xu and H. Yuan, "Smartphone-based integrated PDR/GPS/Bluetooth pedestrian location," Advances in Space Research, vol. 59, no. 3, pp. 877-887, 2017.

[15] G. Ligorio and A. M. Sabatini, "A Novel Kalman Filter for Human Motion Tracking With an Inertial-Based Dynamic Inclinometer," IEEE Transactions on Biomedical Engineering, vol. 62, no. 8, pp. 2033-2043, 2015.

[16] J. Li, M. Guo and S. Li, "An indoor localization system by fusing smartphone inertial sensors and bluetooth low energy beacons," 2017 2nd International Conference on Frontiers of Sensors Technologies (ICFST), pp. 317-321, 2017.

[17] C.-T. Chao, M.-H. Chung, J.-S. Chiou and C.-J. Wang, "A Simple Interface for 3D Position Estimation of a Mobile Robot with Single Camera," Sensors, vol. 16, no. 4, 2016.

[18] B.-C. Huang, J. Hsu, E. T.-H. Chu and H.-M. Wu, "ARBIN: Augmented Reality Based Indoor Navigation System," Sensors, vol. 20, no. 20, 2020.

[19] J. Li, C. Wang, X. Kang and Q. Zhao, "Camera localization for augmented reality and indoor positioning: a vision-based 3D feature database approach," International Journal of Digital Earth, vol. 13, no. 6, 2020.

[20] F. Che, Q. Z. Ahmed, P. I. Lazaridis, P. Sureephong and T. Alade, "Indoor Positioning System (IPS) Using Ultra-Wide Bandwidth (UWB) - For Industrial Internet of Things (IIOT)," Sensors, 2023.

[21] G. Caso, M. T. P. Le, L. D. Nardis and M.-G. D. Benedetto, "Performance Comparison of WiFi and UWB Fingerprinting Indoor Positioning Systems," Technologies, vol. 6, no. 1, 2018.

[22] Z. Hao, B. Li and X. Dang, "A Method for Improving UWB Indoor Positioning," Mathematical Problems in Engineering, p. 17, 2018.

[23] M. Ridolfi, S. Vandermeeren, J. Defraye, H. Steendam, J. Gerlo, D. D. Clercq, J. Hoebeke and E. D. Poorter, "Experimental Evaluation of UWB Indoor Positioning for Sport Postures," Sensors, vol. 18, no. 1, 2018.

[24] P. Lou, Q. Zhao, X. Zhang, D. Li and J. Hu, "Indoor Positioning System with UWB Based on a Digital Twin," Sensors, vol. 22, no. 16, 2022.

[25] B. Yang, J. Li, Z. Shao and H. Zhang, "Robust UWB Indoor Localization for NLOS Scenes via Learning Spatial-Temporal Features.," IEEE Sensors Journal, vol. 22, no. 8, pp. 7990-8000, 2022.

[26] C. Jiang, S. Chen, Y. Chen, D. Liu and Y. Bo, "An UWB Channel Impulse Response De-Noising Method for NLOS/LOS Classification Boosting," IEEE Communications Letters, vol. 24, no. 11, pp. 2513-2517, 2020.

[27] H. Xu, Y. Ding, P. Li, R. Wang and Y. Li, "An RFID Indoor Positioning Algorithm Based on Bayesian Probability and K-Nearest Neighbor," Sensors, vol. 17, no. 8, 2017.

[28] P. Tan, T. H. Tsinakwadi, Z. Xu and H. Xu, "Sing-Ant: RFID Indoor Positioning System Using Single Antenna with Multiple Beams Based on LANDMARC Algorithm," Applied Science, vol. 12, no. 13, 2022.

[29] Z. Manman, L. Peng, X. He and W. Ruchuan, "RFID Indoor Positioning Based on AP Clustering and Improved Particle Swarm Algorithm," Journal of Sensors. Hindawi, 2022.

[30] J. Mi and Y. Takahashi, "Design of an HF-Band RFID System with Multiple Readers and Passive Tags for Indoor Mobile Robot Self-Localization," Sensors, vol. 16, no. 8, 2016.

[31] D. Bragin, E. Kostyuchenko, V. Faerman, A. Kobzev and I. Sidorov, "Comparison of Technologies of Local Patient Positioning," International Journal of Advanced Research in Engineering and Technology (IJARET), vol. 12, no. 1, pp. 362-386, 2021.

[32] Z. Wang, A. Xuan, Z. Liu and Y. Alfadhl, "Research on RFID Positioning Algorithm with Single Antenna," in 2019 8th Asia-Pacific Conference on Antennas and Propagation (APCAP), Incheon, Korea (South), 2019.

[33] L. M. Ni, Y. Liu, Y. C. Lau and A. Patil, "LANDMARC: indoor location sensing using active RFID," in Proceedings of the First IEEE International Conference on Pervasive Computing and Communications, Fort Worth, TX, USA, 2003.

[34] S. He and S. -H. G. Chan, "Wi-Fi Fingerprint-Based Indoor Positioning: Recent Advances and Comparisons," IEEE Communications Surveys & Tutorials, vol. 18, no. 1, pp. 466-490, 2015.

[35] M. U. Ali, S. Hur and Y. Park, "Wi-Fi-Based Effortless Indoor Positioning System Using IoT Sensors," Sensors, vol. 19, no. 7, 2019.

[36] D. Ko, M. Kim, K. Son and D. Han, “Passive Fingerprinting Reinforced by Active Radiomap for WLAN Indoor Positioning System,” IEEE Sensors Journal, vol. 22, no. 6, pp. 5238-5247, 2022.
[37] H. Ye and J. Peng, “Robot Indoor Positioning and Navigation Based on Improved WiFi Location Fingerprint Positioning Algorithm,” Wireless Communications and Mobile Computing. Hindawi, vol. 2022, 2022.
[38] Z. Zhang, M. Lee and S. Choi, “Deep-Learning-Based Wi-Fi Indoor Positioning System Using Continuous CSI of Trajectories,” Sensors, vol. 21, no. 17, 2021.
[39] P. Y. Chan, J.-C. Chao and R.-B. Wu, “A Wi-Fi-Based Passive Indoor Positioning System via Entropy-Enhanced Deployment of Wi-Fi Sniffers,” Sensors, vol. 23, no. 3, 2023.
[40] “Bluetooth Core Specification Versions: 4.0,” Bluetooth SIG, 2010. [Online]. Available: https://www.bluetooth.com/specifications/specs/core-specification-4-0/. [Accessed 29 December 2023].
[41] “From Proximity to Precise Positioning,” Bluetooth SIG, [Online]. Available: https://www.bluetooth.com/learn-about-bluetooth/solutions/location-services/. [Accessed 29 December 2023].
[42] K. Maneerat and K. Kaemarungsi, “Performance Improvement Design of Bluetooth Low Energy-Based Wireless Indoor Positioning Systems,” Mobile Information Systems, vol. 2020, 2020.
[43] S. Rozum, J. Kufa and L. Polak, “Bluetooth Low Power Portable Indoor Positioning System Using SIMO Approach,” in 42nd International Conference on Telecommunications and Signal Processing (TSP), Budapest, Hungary, 2019.
[44] P. Sthapit, H.-S. Gang and J.-Y. Pyun, “Bluetooth Based Indoor Positioning Using Machine Learning Algorithms,” in 2018 IEEE International Conference on Consumer Electronics - Asia (ICCE-Asia), JeJu, Korea (South), 2018.
[45] L. Bai, F. Ciravegna, R. Bond and M. Mulvenna, “A Low Cost Indoor Positioning System Using Bluetooth Low Energy,” IEEE Access, vol. 8, pp. 136858-136871, 2020.
[46] A. Loganathan, N. S. Ahmad and P. Goh, “Self-Adaptive Filtering Approach for Improved Indoor Localization of a Mobile Node with Zigbee-Based RSSI and Odometry,” Sensors, vol. 199, no. 21, 2019.
[47] Z. Y. Dong, W. M. Xu and H. Zhuang, “Research on ZigBee Indoor Technology Positioning Based on RSSI,” Procedia Computer Science, vol. 154, pp. 424-429, 2019.
[48] C.-H. Cheng and S.-J. Syu, “Improving area positioning in ZigBee sensor networks using neural network algorithm,” Microsystem Technologies, vol. 27, p. 1419–1428, 2019.
[49] X. Li, J. Wang, C. Lui, L. Zhang and Z. Li, “Integrated WiFi/PDR/Smartphone Using an Adaptive System Noise Extended Kalman Filter Algorithm for Indoor Localization,” ISPRS International Journal of Geo-Information, vol. 5, no. 2, 2016.
[50] Z. Li, C. Liu, J. Gao and X. Li, “An Improved WiFi/PDR Integrated System Using an Adaptive and Robust,” ISPRS International Journal of Geo-Information, vol. 5, no. 12, 2016.
[51] X. Li, J. Wang and C. Liu, “A Bluetooth/PDR Integration Algorithm for an Indoor Positioning System,” Sensors, vol. 15, no. 10, pp. 24862-24885, 2015.
[52] C. Lu, H. Uchiyama, D. Thomas, A. Shimada and R.-i. Taniguchi, “Indoor Positioning System Based on Chest-Mounted IMU,” Sensors, vol. 19, no. 2, 2019.
[53] Y. Zhu, X. Luo, S. Guan and Z. Wang, “Indoor Positioning Method Based on WiFi/Bluetooth and PDR Fusion Positioning,” 13th International Conference on Advanced Computational Intelligence (ICACI), pp. 233-238, 2021.
[54] G. T. Lee, S. B. Seo and W. S. Jeon, “Indoor Localization by Kalman Filter based Combining of UWB-Positioning and PDR,” in 2021 IEEE 18th Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA, 2021.
[55] C. Jiang, J. Shen, S. Chen, Y. Chen, D. Liu and Y. Bo, “UWB NLOS/LOS Classification Using Deep Learning Method,” IEEE Communications Letters, vol. 24, no. 10, pp. 2226-2230, 2020.