Chapter

A Comparative Analysis and Review of Indoor Positioning Systems and Technologies

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Abstract

This chapter presents a comparative analysis and review of indoor positioning systems, both from an algorithm and a technology point of view. It sheds light on the evolving landscape of location-based services within confined spaces. The review encompasses a diverse range of technologies employed in indoor positioning systems, including Wi-Fi-based systems, Bluetooth low-energy solutions, radio frequency identification technologies, ultra-wideband, inertial measurement units, visual-based systems, and sensor fusion approaches amongst many others. By summarising a multitude of research findings and technological advancements, the chapter offers insights into the strengths, limitations, and emerging trends within the field. Furthermore, it critically assesses the performance metrics of various indoor positioning systems, thus providing a comprehensive guide for researchers, developers, and practitioners. The comparative analysis delves into the practical implications of these systems, by considering factors such as design and deployment cost, power efficiency, and adaptability to different indoor environments. The main types of signal acquisition and position estimation techniques used in indoor positioning systems are discussed, while providing the advantages and disadvantages of each approach. This chapter aims to contribute to the advancement of indoor positioning technology, by offering valuable perspectives for future research directions and practical applications.

Keywords: location-based services, literature survey, communication protocols, algorithms, adaptability, sensing

1. Introduction

An indoor positioning system (IPS) is a system that continuously and in real time determines the position of a person or an object in an indoor environment [1]. This system is designed to work within the confines of a building or a structure while relying on various technologies, algorithms, and techniques to accurately track and locate targets. In recent years, there has been a growing interest in IPS research and development [2]. Various IPSs have been designed to provide accurate information about the position of a person or an object inside a building [3]. These systems have various applications, ranging from warehouse management, healthcare tracking, navigation assistance for blind individuals, and emergency response operations [2, 4, 5]. The evolution of IPS has paved the way for the development of indoor location-based services (LBS), where applications are built around the position estimation of an object or a person [6]. Geofencing, asset tracking, and targeted advertising are just a few examples of LBS that can be enhanced by the implementation of IPS. These services utilise the precise location data provided by IPS to offer a personalised experience, improve operational efficiency, and optimise resource management [2, 7]. Although a number of literature review articles have already been published [2, 3, 6–12], this work aims to present an updated and complete overview together with a comparative analysis of IPS, focusing on both the algorithms and the technologies. This review aims to shed light on the evolving landscape of LBS within confined spaces, considering a diverse range of IPS technologies, including Wi-Fi-based systems, Bluetooth low-energy solutions, radio frequency identification (RFID) technologies, ultra-wideband (UWB), inertial measurement units, visual-based systems, and sensor fusion approaches, amongst others.

While outdoor positioning systems (OPSs), such as the global position system (GPS), are widely used for LBS in open and outdoor environments, they are not suitable for indoor use. This is primarily due to the limitations of signal penetration and accuracy in indoor spaces [2]. OPSs rely on satellite signals to determine the location of a person or an object. However, when these signals enter the indoor environments, they often experience signal degradation or complete blockage due to the presence of walls, ceilings, and other physical obstructions. This can result in inaccurate and unreliable positioning information within indoor settings. Therefore, IPS has emerged as a separate field, focusing on developing technologies and algorithms that can accurately locate objects or persons within confined spaces. In contrast, IPS is specifically designed to overcome these challenges by utilising alternative technologies that are better suited for enclosed spaces. These technologies can provide more precise and reliable indoor location information. One or more technologies can be employed to compensate for the limitation of a single technology.

Understanding the distinct differences between outdoor and indoor positioning systems is crucial for developing effective and accurate LBS, which are tailored to specific environments. By leveraging the strengths of indoor positioning technologies, businesses and organisations can optimise operational efficiency, enhance safety measures, and improve the user experience within indoor spaces [3]. The review presented in this chapter summarises a multitude of research findings and technological advancements, providing insights into the strengths, limitations, and emerging trends within the field of IPS. Employing a combination of sophisticated sensors with wireless communication has introduced new applications, which can simplify the daily activities of human beings, increase independence, and improve the quality of life [13]. IPS has gained significant attention due to their potential to revolutionise various industries and improve the overall user experience within confined spaces [9].

In addition to the introductory section, this chapter is divided as follows. Section 2 discusses the need for IPS and its targeted applications, while highlighting the challenges and opportunities. In addition, Section 2 lists the performance metrics that are used to characterise and compare different IPSs in a fair way. Section 3 delves into the five main types of signal acquisition techniques and algorithms, while providing the advantages and disadvantages of each approach. Section 4 discusses different position estimation techniques such as triangulation, trilateration, finger printing, and vision analysis. Section 5 presents and compares the various technologies employed in IPS. Finally, Section 6 discusses the potential research directions and future applications of IPS and Section 7 provides a few concluding remarks.

2. Indoor positioning systems

In order to obtain the physical position of an object or a person, two phases are involved in an IPS: the signal acquisition phase and the position estimation phase, as shown in **Figure 1**. In the first phase, the communication system attached to the object, or a person transmits and receives signals to and from a number of reference nodes placed at known locations within the indoor environment [14]. A particular property of these signals, such as the signal strength or the time-of-flight, is then measured and used in the position estimation phase to calculate the target's coordinates. There are several types of signals that can be utilised for indoor positioning, each with its own strengths, limitations, and properties [10] as will be discussed in Section 5. In addition, since signal measurement in practical systems is only accurate to a certain degree, various algorithms and techniques are employed to improve the accuracy and reliability of IPS [6], including optimisation-based statistical techniques that filter out measurement errors and noise.

The need for IPS arises from the numerous applications and the benefits it offers in a variety of industries and scenarios [7]. These applications range from private home use, such as tracking items and as an aid for the elderly or disabled individuals, to public buildings where IPS helps visually impaired individuals to navigate indoors, track people in crowded places, and enhance security measures [7]. IPS also plays a crucial role in medical environments, where they can be used for tracking patients, preventing the theft of expensive equipment, and aiding doctors and nurses in their daily tasks [7]. Furthermore, IPSs are increasingly being adopted in industries such as manufacturing, robotics, and automation. Applications such as robotic guidance, smart factories, and cooperative robotics are quite common. The emergence of smartphones has further accelerated the demand for IPS. Smartphones have become ubiquitous and are equipped with various technologies such as Wi-Fi and Bluetooth radios, which can be utilised for indoor positioning [2]. Furthermore, the rapid growth of e-commerce and online shopping has created a need for accurate IPS in retail environments [3]. IPS has the potential to revolutionise the retail industry by providing personalised shopping experiences, targeted advertisements, and efficient inventory management [2].

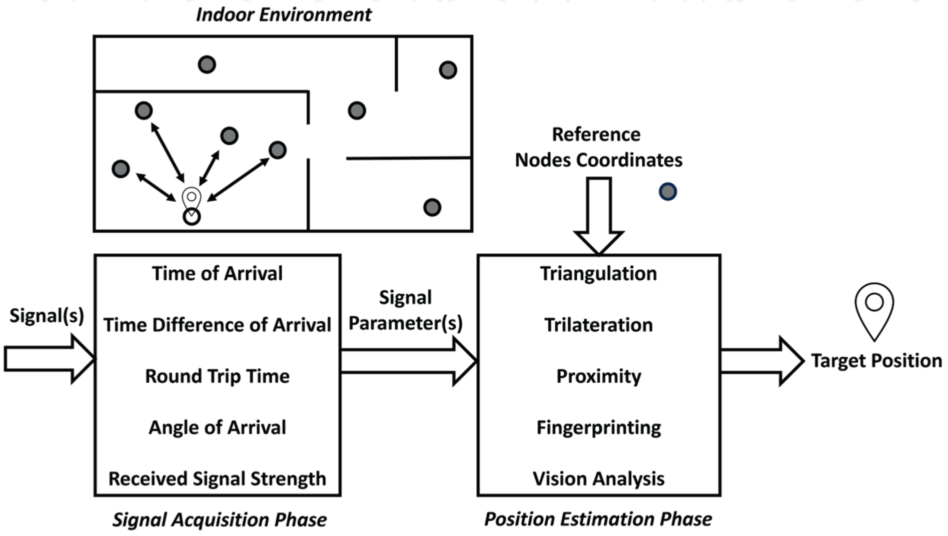

Figure 1.
Signal acquisition and position estimation in indoor positioning systems.

2.1 Challenges and opportunities

IPSs face unique challenges compared to OPS, since they feature unique characteristics that are different from those of OPS. The primary challenge faced by IPS is the presence of obstacles and signal interference [2]. The presence of signal reflections and multipath propagation in indoor environments can lead to signal distortion and destructive interference, affecting the accuracy and the reliability of the position estimation. Indoor positioning applications often require a higher accuracy and precision in comparison with OPS applications, to efficiently handle small areas and existing obstacles. The presence of walls, furniture, and other physical structures can obstruct or weaken signals, leading to signal loss and degradation [6]. Additionally, electromagnetic interference generated by other electronic devices and wireless networks in proximity can complicate the positioning process. Various techniques and algorithms have been developed, to overcome these challenges and improve the accuracy and reliability of IPS [15]. These techniques and algorithms involve signal measurement, signal processing, and fusion of multiple signals [3]. Furthermore, the limited availability of line-of-sight (LOS) signal propagation, like in the case of GPS, impacts the performance of IPS.

Nonetheless, there are several characteristics within indoor environments that facilitate positioning [2]. In an indoor environment, a person or an object moves at a relatively slower speed with respect to an outdoor scenario. In addition, a small area facilitates the position monitoring due to a predetermined infrastructure together with small variations in ambient parameters such as temperature, humidity, and air circulation. In indoor environments, signals from technologies like Wi-Fi, Bluetooth, and RFID can reflect off surfaces such as walls, floors, and ceilings. While this can create challenges in signal measurement and analysis, it also provides opportunities for triangulation and signal enhancement, leading to more precise location determination [12].

Indoor environments often have a fixed infrastructure which aids the strategic placement of access points, beacons, and RFID readers for enhanced network connectivity or operational purposes. These infrastructure elements can be used by IPS to establish reference points and enhance location accuracy [16]. Compared to outdoor spaces, indoor environments offer a more controlled setting, allowing for the optimisation of signal propagation and reception. This control can be instrumental in minimising signal interference and improving the overall performance of indoor positioning systems [10, 12, 15]. IPS can be integrated with building management systems, security systems, or smart environment technologies. This provides holistic functionalities that enable efficient resource utilisation, enhanced security measures, and the seamless coordination of various indoor processes [7, 12]. IPS can also be integrated with Internet of Things (IoT) devices and sensors within indoor environments, enabling the collection of real-time data for various applications such as smart homes, healthcare monitoring, asset tracking, and energy [17]. Indoor environments generally have reliable power sources and network connectivity, providing a stable infrastructure for the deployment and operation of IPS. This accessibility facilitates the continuous operation of positioning systems with minimal downtime [7, 17]. Understanding these characteristics can aid in the development and the deployment of IPS which are tailored to specific indoor environments. Ultimately accuracy, reliability, and effectiveness are enhanced, thus leading IPS to support a wide range of applications and scenarios.

2.2 Performance metrics

In this section, different performance metrics of IPS are presented and discussed. Performance metrics play a crucial role in assessing the suitability of a system before designing or deploying it for a particular application. Such metrics are used to characterise and compare different IPSs in a fair way and provide insights into their strengths and limitations.

2.2.1 Accuracy and precision

Accuracy refers to the closeness of the measured positions to the true positions. The accuracy of an IPS is the mean Euclidean distance between the estimated position and the true position [3, 10]. It is essential to ensure that the location data provided by the IPS is reliable and can be used for critical applications such as emergency response or asset tracking. Accuracy is still an open challenge for researchers in this field [3]. Precision is the consistency or repeatability of the position measurements. High precision implies that the system can consistently determine the same position for an object or person in multiple measurements. This is crucial for applications that require fine-grained location information and reliable tracking such as indoor navigation and augmented reality (AR) [18].

2.2.2 Availability and reliability

Availability refers to the percentage of time that the system is operational and can provide accurate location information. Availability is generally classified into three different levels: low availability (less than 95%), regular availability (more than 99%), and high availability (more than 99.9%) [19]. It is essential for applications that require continuous and uninterrupted positioning, such as real-time asset tracking and emergency response systems. Availability can be limited by both random factors such as communication congestion and periodic factors such as routine maintenance. Reliability measures the consistency of the system in providing accurate results over time. A reliable IPS ensures that the location data remains consistent and trustworthy even with changes in environmental conditions or user mobility.

2.2.3 Latency

Latency is another important metric for IPS, representing the time delay between the instant when a position measurement is requested and the instant when the result is available. Low latency is crucial for time-sensitive applications, such as interactive LBS and real-time tracking, where immediate responsiveness is essential for excellent user experience and operational efficiency [12].

2.2.4 Coverage area

The coverage area indicates the physical space within which the IPS can provide accurate location information. Each IPS has its own coverage area, which can vary from a small room to an entire building [3]. Nonetheless, designing an IPS that features a coverage of more than 60 metres is still very challenging. The coverage range depends on the technology used and the infrastructure in place [6]. For example, Wi-Fi-based systems generally have a coverage range of up to 30 meters, while RFID technologies may have shorter ranges of around 5 meters. Hence, short-range technology such as RFID may be suitable for localised applications, while long-range technologies like Wi-Fi can provide coverage for larger areas [3]. Thus, short-range technology needs more devices to cover a given area in comparison with long-range technology.

2.2.5 Scalability, complexity, and robustness

Scalability refers to the ability of the system to accommodate an increasing number of tracked objects or users without compromising performance. A scalable IPS should maintain its accuracy and reliability, as the number of tracked entities grows. This ensures its suitability for diverse environments and applications. Scalability also refers to the ability of the system to expand its coverage area or range by adding more infrastructure components or devices [20, 21]. Complexity, on the other hand, refers to the intricacy and sophistication of the IPS. A complex system may require advanced algorithms, multiple sensors, and a robust infrastructure to operate effectively. Thus, complexity can be attributed to the algorithmic implementation, whether it is distributed or centralised, the hardware requirements of the IPS including the computational platform and peripheral devices, and the overall operation factors such as installation and maintenance [22]. Robustness is another important aspect influencing the complexity of an IPS and refers to the ability to handle variations and external factors that may affect the performance of an IPS [3]. In relation to this, the adaptiveness of an IPS refers to its capability to adjust to dynamic environmental conditions, such as changes in signal interference, infrastructure layout, or user mobility patterns. An adaptive system can optimise its performance and accuracy by dynamically adapting its algorithms, signal processing techniques, or infrastructure configuration in response to varying conditions. This ensures reliable and robust operation in real-world indoor environments [6].

2.2.6 Power consumption and efficiency

Power consumption and efficiency are significant considerations for IPS, especially for battery-powered devices and energy-efficient infrastructure. Minimising power consumption while maintaining high-performance levels is essential for prolonging the operational lifespan of devices and minimising maintenance needs such as battery replacement. Furthermore, power-efficient IPS can also have a positive impact on environmental sustainability by reducing energy consumption.

2.2.7 Cost effectiveness

Cost effectiveness is an important factor to consider when evaluating IPS. It involves assessing the balance between the cost of implementing and maintaining the system and the benefits it provides in terms of improved operational efficiency, enhanced user experience, and overall value to the organisation or end users. Factors such as initial setup costs, infrastructure requirements, maintenance expenses, and potential return-on investment need to be considered when determining the cost-effectiveness of an IPS for a specific application [6, 23, 24]. The cost of an IPS can be evaluated across different dimensions including financial, time, space, and energy [2]. Furthermore, the cost effectiveness of an IPS can also be influenced by factors such as scalability and complexity [3]. Certain IPS employs passive RFID tags that are more cost-effective due to their low-energy consumption and simple implementation, while others reuse existing infrastructure such as Wi-Fi networks, making them more cost-effective compared to systems that require the installation of dedicated hardware.

2.2.8 Privacy, security, and user experience

Privacy, security, and user experience are increasingly becoming significant considerations in the design and deployment of IPS [23]. Privacy concerns arise from the collection and use of location data, especially in scenarios where individuals or assets are being tracked. It is important for IPS to implement privacy-preserving measures and comply with relevant regulations to ensure the protection of sensitive location information against intrusion, theft, or misuse [24]. User experience encompasses the ease of use, accuracy, and the overall value of the LBS provided by the IPS. A positive user experience is essential for the widespread acceptance and adoption of IPS, making it a crucial performance metric. Furthermore, to improve the user experience, IPS should aim to provide real-time and seamless positioning information in a non-intrusive way, while maintaining a high level of security and privacy.

3. Signal acquisition techniques and algorithms

This section discusses the main types of signal acquisition techniques and algorithms while providing the advantages and disadvantages of each approach. These techniques can be generally divided into three categories: time-based acquisition, angle-based acquisition, and received signal strength acquisition.

3.1 Time-of-arrival

Time-of-arrival (TOA) or time-of-flight (TOF) is a signal acquisition technique that measures the time it takes for a signal to travel from the transmitter node to the receiver or target node. This technique relies on accurately measuring the time delay t_d between the transmission and the reception of the signal, to determine the distance d between the nodes, by knowing *a priori* the corresponding signal propagation velocity v_p [25, 26].

$$d = t_d \times v_p \tag{1}$$

This information can then be used to triangulate the position of the target node. The advantages of TOA include its high accuracy and precision in determining the distance between nodes. While TOA-based techniques are based on a simple principle (Eq. 1), they can be sensitive to factors such as signal reflections and multipath effects, which can introduce errors in the distance measurements. In order to mitigate the impact of these factors, TOA techniques require synchronisation between the transmitter and the receiver nodes [27]. A well-synchronised clock is crucial for accurate TOA measurements. The work [28] presented fundamental bounds for an ideal and multipath environment while highlighting the main sources of error for

TOA ranging. TOA is often used with UWB technology, which utilises pulses of short duration to filter out signal reflections and improve overall performance. Another disadvantage is its high computational cost, due to the need for high-resolution time measurements and complex calculations to determine the distances between nodes. TOA-based algorithms have been used to locate objects or devices in various applications [26]. An underground coal mine worker localisation system was designed using this technique together with UWB technology to track the position of workers for safety purposes [9]. A novel UWB-based navigation system for mobile robot tracking was presented in Ref. [29].

3.2 Time difference-of-arrival

Time difference-of-arrival (TDOA) relies on measuring the difference in arrival times between two different types of signals transmitted from the transmitting node to the receiver node [27]. By comparing the time difference between the arrivals of these signals at the receiver, the transmitting node location can be deduced by using Eq. (2):

$$t_{d1} - t_{d2} = \frac{d}{v_{p1}} - \frac{d}{v_{p2}} \tag{2}$$

where v_{p1} and v_{p2} are the propagation velocities of the two different signals and t_{d1} and t_{d2} are the time delays taken by the two respective signals to travel a distance d between the transmitting node and the receiving node. Another approach to TDOA-based algorithms is based on measuring the TDOA of a single signal sent by an object or person and received by three or more receivers [30]. Each difference of arrival time produces a hyperbolic curve on which the target location lies. One needs prior information to eliminate the position ambiguity caused by the intersection of multiple hyperbolic curves [31]. The advantage of TDOA-based techniques is their ability to provide accurate positioning measurements, even in environments with severe multipath fading [27]. For instance, multi-carrier signals can be used to reduce the performance degradation due to multipath propagation within indoor environments [32, 33]. The localisation accuracy of TDOA-based techniques is highly dependent on the synchronisation of the clocks at the receiver nodes. Nonetheless, precise synchronisation between the target and the base station is not required as in TOA [9, 34]. One limitation is the need for multiple receivers to accurately measure the time difference of arrival. Furthermore, TDOA-based algorithms require significant bandwidth due to the need for multiple receivers to share data and cooperate in determining the location of the transmitter [35]. TDOA-based algorithms have also been combined with other techniques to enhance the accuracy of IPS as reported in Refs. [36, 37]. Apart from using RF technologies, TDOA can also be employed in visible light communication systems as proposed in Ref. [38].

3.3 Round trip time

Even though TOA and TDOA are employed in many IPS, they are still limited by strict synchronisation requirements [39] which increase the deployment and the maintenance costs to guarantee adequate accuracy. Round trip time (RTT) is another technique which measures the time t_{RTT} taken by a signal to travel from a transmitting node to a receiving node and back again. RTT was proposed as an alternative technique to mitigate the synchronisation problem of TOA [40, 41]. In RTT, the distance d is calculated using Eq. (3):

$$d = \frac{\left(t_{RTT} - \delta t\right) \times v_p}{2} \tag{3}$$

where δt is the processing time incurred by the hardware within the receiving node and v_{p} is the signal velocity of propagation. In RTT, only one node measures the transmitted and arrival time instead of using two local clocks in both the transmitting and receiving nodes as in TOA. Nonetheless, RTT increases the computational time complexity of the system to $O(n^2)$, where the complexity of this approach rises quadratically as the number of nodes n increases. The system requires n iterations to determine the target node position *via* message relaying with the other nodes. Time measurements are also impacted by several uncertainty factors including the phase noise or the jitter of the clock [8]. Given the limitations of RTT, the issue of synchronisation in time-based approaches deserves further investigation since RTT solves it only to a certain extent, while factoring in other considerations and restrictions in the implementation.

3.4 Angle-of-arrival

Angle-of-arrival (AOA)-based methods make use of the nodes' capability to measure the angle of arrival of signals [1, 2, 9, 42]. This information is used to determine the position of an object, where LOS conditions are present. Only two beacons are required to estimate the position in a two-dimensional (2D) plane, while three or more beacons are needed for three-dimensional (3D) positioning or in case one needs to improve the accuracy. The AOA technique estimates the position of an object or a person by comparing either the signal amplitude or the carrier-phase across multiple antennas. The target's receiver position can be estimated *via* the intersection of the angle line from each signal source. Since the transmitter timing information is encoded in this signal, the receiver does not need to maintain synchronisation with the clock of any beacon [3]. On the other hand, directional antennas [43] or antenna arrays are needed, thus increasing the cost. AOA is affected by multipath or non-line-of-sight (NLOS) propagation and reflections, which can lead to inaccuracies in the estimated position since the direction of signal arrival is altered. AOA accuracy is also influenced by the range, and the antenna array geometry has a major impact in the estimation algorithm [44]. Due to these limitations, AOA techniques are often combined with other techniques such as TDOA [45] or adopt a cooperative approach. Such approach integrates pairwise AOA information amongst all sensor nodes rather than relying solely on anchor nodes [46].

3.5 Received signal strength

Received signal strength (RSS)-based methods rely on measuring the strength of radio signals received from beacons or access points to estimate the distance between the target object and the reference points [9]. The distance is inversely proportional to the signal strength and is measured based on the attenuation due to the signal propagation by using an empirical mathematical model [8]. This model depends on the number of obstacles, attenuation factors, and routing factors. RSS localisation either employs a propagation model algorithm or a fingerprinting algorithm [47]. RSS is simpler to use when compared to AOA or TDOA. It does not need dedicated hardware at the mobile station, apart from a wireless network interface card [3], and RSS algorithms tend to involve less communication traffic. This provides an improved channel access control and position accuracy [9]. RSS-based methods do not require synchronisation but need at least three reference nodes for a 2D space and at least four reference nodes for a 3D space. LOS propagation is preferred since signal attenuation is affected by obstacles and multipath propagation, which can distort the signal strength and lead to inaccuracies in the estimated position [48]. Moreover, the accuracy of RSS-based methods is highly dependent on the environment in which they are deployed, making it hard to establish an accurate propagation model [3, 9], especially in dynamic scenarios.

4. Indoor position estimation techniques

The position estimation in IPS involves determining the location of a target object or a person based on the measurements obtained through the various techniques discussed in Section 3 [8]. This process employs various mathematical algorithms and techniques which can be categorised into different approaches, including trilateration, triangulation, fingerprinting, proximity sensing, and vision analysis [3]. Statistical techniques such as maximum likelihood estimation (MLE) are often used to improve and augment the accuracy in a noisy environment [8], particularly in the context of trilateration-based positioning [49]. MLE is also used to limit the problem of synchronisation by predicting uncertain bias parameters in the time domain [50, 51].

4.1 Trilateration

Trilateration determines the location of a target T by measuring its distance from at least three reference points as shown in **Figure 2**.

The distances are typically determined using techniques such as TOA, TDOA, or RSS. The trilateration algorithm then uses these distance measurements to calculate the coordinates of the target in a 2D or 3D space. By knowing *a priori*, the coordinates of the reference nodes RN_1, RN_2, and RN_3, and estimating the corresponding distance from each reference node to the target node (d_1, d_2, and d_3), one can obtain the following three circle equations (Eq. 4):

$$\begin{aligned}(x_1 - x)^2 + (y_1 - y)^2 &= d_1^2 \\ (x_2 - x)^2 + (y_2 - y)^2 &= d_2^2 \\ (x_3 - x)^2 + (y_3 - y)^2 &= d_3^2\end{aligned} \tag{4}$$

which provide the unknown coordinates of the target *(x,y)* by finding the intersection of the three circles [8]. The work in Ref. [52] showed that by considering

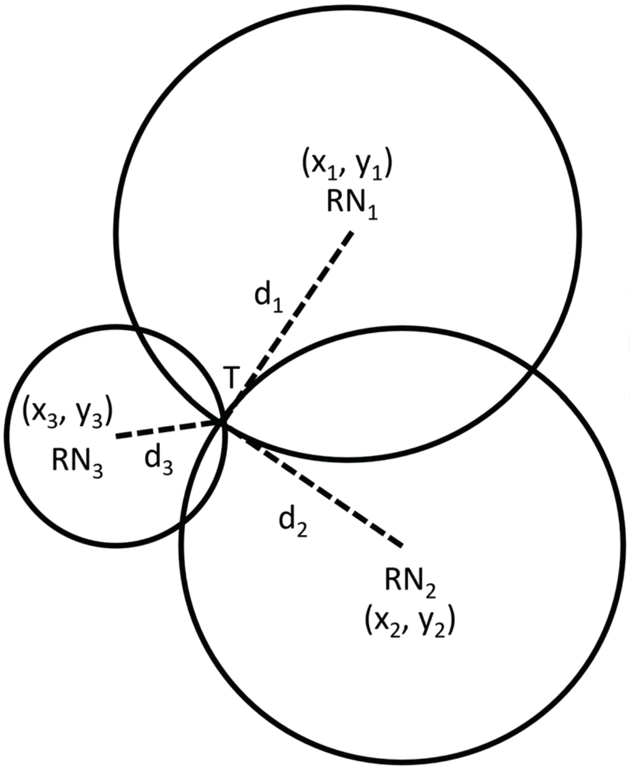

Figure 2.
Visualisation of the trilateration-based position estimation for a 2D space.

the layout of the three reference nodes, one can improve localisation performance, particularly if RN_1, RN_2, and RN_3 are placed on the vertices of equilateral triangles. In addition, by considering the influence of the noise on the measurements and using different confidence coefficients for the nodes, it is possible to further improve the quality of the trilateration [53].

4.2 Triangulation

Triangulation is based on measuring angles, by using AOA techniques instead of measuring distances as in trilateration, to determine the position of an object relative to multiple reference points as shown in **Figure 3**.

Compared to trilateration, only two reference nodes (RN_1 and RN_2) are required in a 2D space triangulation instead of three reference nodes. The intersection of a pair of angle direction lines given by Eq. (5):

$$\frac{y-y_1}{x-x_1}=\tan(\theta_1) \qquad \frac{y_2-y}{x_2-x}=\tan(\theta_2) \tag{5}$$

is used to determine the coordinates of the target position *(x,y) via* the geometric properties of triangles and predetermined coordinates of the reference nodes (x_1, y_1) and (x_2, y_2), after measuring angles θ_1 and θ_2 [20, 54]. Triangulation can be transformed to trilateration, because the distance between the nodes is related to the angles between them [8].

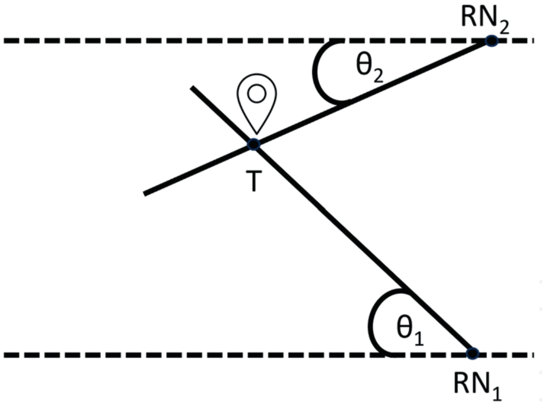

Figure 3.
Visualisation of the triangulation-based position estimation for a 2D space.

4.3 Proximity location sensing

Proximity location sensing is a technique that estimates the location of a target object with respect to a known position or area, by using a particular physical phenomenon [55]. Several detectors are placed at predetermined locations.

Proximity sensing relies on either the detection of physical contact or the use of radio sensors with a limited range or automatic identification systems [54]. Physical contact can be detected using sensors such as pressure sensors, inductive sensors, capacitive field sensors, or touch sensors. Proximity sensing can be alternatively implemented by continuously monitoring wireless access points (Wi-Fi, Bluetooth, or cellular) and detect the presence of a mobile device when it gets into range. One can also infer the location of a mobile object by using automatic identification systems such as point-of-sale terminals, computer login registries, or land-line telephone records [3]. If these devices have a known location and are accessed by the mobile object by either scanning a RFID label or interrogating a tag, one can get its location. Advantages of proximity location sensing include its simplicity and low cost, whereas its disadvantages include limited range, the inability to provide precise location information, and user dependability.

4.4 Fingerprinting

Fingerprinting relies on the matching of signal characteristics, such as RSS, at different locations within an indoor environment either using deterministic or using probabilistic algorithms. Prior to its deployment, a database of signal strength measurements at various known locations within the indoor environment is created, during the so-called training or offline phase. The construction of a radio map is carried out by sub-dividing the area into cells by using a floor plan. RSS values of radio signals at different positions are measured for a finite amount of time [3, 20, 55, 56]. Subsequently, while operating in the online stage, the system uses the currently observed RSS values and compares them to those stored in the database to identify the location of the target object based on its measured signal strength [12]. Advantages of fingerprinting include its ability to provide highly accurate and precise location information, especially in environments where signal propagation characteristics are well modelled and stable. It can also accommodate various environmental factors, such NLOS propagation, which can affect other localisation methods. However, fingerprinting also has some limitations. Creating, maintaining, and updating the fingerprint database can be labour-intensive, resource-intensive, and time-consuming, especially in dynamic environments where signal propagation characteristics may change. For instance, the RSS values can be easily affected by reflection, scattering, or diffraction propagation phenomena [15, 56].

4.5 Vision analysis

Vision analysis uses cameras or vision sensors to capture images or video footage of the indoor environment and then analysing them to estimate the position of a target object. Real time images captured by one or multiple cameras fixed within the IPS tracking area are processed using computer vision algorithms. These can detect and track objects based on their visual features such as colour, shape, or texture. The observed target images are compared against a database of known images or patterns. Vision positioning techniques can also provide useful location context information employed by LBS [55].

5. Indoor positioning technologies

This section provides an overview of some of the commonly used IPS technologies, while highlighting their respective strengths and limitations. When selecting the appropriate technology for a particular application, it is important to consider the performance metrics discussed in Section 2.2 to achieve the best trade-off between complexity, cost, and performance. In addition, complementary technologies can be used to take advantage of their distinctive advantages and compensate for any limitations [3, 9]. IPS technologies can be classified according to different criteria. These criteria include the type of sensors used, whether IPSs are networked-based or not, whether they require existing hardware located in the building or are self-contained and the physical medium used to determine the position of a target [3].

5.1 Radio frequency identification (RFID)

RFID uses radio waves to automatically identify objects or people in large systems [2]. RFID-based IPS rely on small tags that can be attached to objects or worn by individuals [3]. These passive or active tags contain unique identification information and can be read by RFID readers placed throughout the indoor environment [2]. RFID tags consist of a microchip and an antenna, whereas the RFID reader consists of an antenna, transceiver, power supply, a processor, and an interface to a dedicated server [3]. The main advantage of RFID is that it may penetrate through solid non-metallic objects and does not require LOS propagation. On the other hand, the communication is not intrinsically secure and consumes more power than infrared (IR) devices. In a RFID system, signals can be affected by their antennas, its positioning coverage is generally small, and it is not easy to integrate it in other systems [3]. RFID makes use of proximity and RSS measurement techniques.

5.2 Mobile phone networks

Mobile phone networks such as Global System for Mobile Communications (GSM) have become popular for indoor positioning because they are widely accessible worldwide and have a high rate of usage [9]. This approach relies on the existing infrastructure of base station towers and the signals transmitted between the mobile devices and these towers is used to determine their indoor position. The main advantages of using phone networks are their ubiquity and the fact that they operate on specific licenced bands, thus eliminating the chance of interference from other communication devices [57]. They are also capable of providing coverage in both indoor and outdoor spaces. By analysing the RSS and timing information from multiple towers, these systems can estimate the position of a mobile device within an indoor environment. However, there are some limitations to using phone networks for indoor positioning. The accuracy of mobile phone-based IPS can vary depending on factors such as signal interference, building materials, and the density of the surrounding structures [9, 15]. Additionally, phone networks are primarily designed for communication rather than precise location determination, which can impact the accuracy of indoor positioning.

5.3 Wireless personal area networks - ZigBee and Bluetooth

ZigBee technology is a short-distance and low data rate (around 250 kbps) wireless personal area network (WPAN) standard operating on the IEEE 802.15.4 specification providing network, security, and application support services [3]. ZigBee technology is attractive due to its low power consumption and cost efficiency. ZigBee devices are small and consist of a microcontroller and a multichannel two-way radio. These systems typically involve the deployment of ZigBee anchor nodes throughout the indoor environment, which communicate with mobile devices and exchange information to determine the position by either using RSS [58, 59] or phase shift measurements [3]. Several studies have explored the use of ZigBee technology for indoor positioning [10, 12, 59]. ZigBee-based systems face some challenges including limited range and coverage, as ZigBee signals have a relatively short-range and can be obstructed by walls [9].

Furthermore, Zigbee-based systems may experience interference from other wireless communication systems operating in the same frequency range, resulting in reduced accuracy, since they operate in the unlicensed industrial, scientific, and medical (ISM) radio bands. ZigBee nodes can either be implemented as a full function device (FFD) or a reduced function device (RFD) [3]. A FFD implements the full protocol set and acts as a network coordinator. On the other hand, RFDs are devices capable to implement a minimal version of the protocol [58, 60].

Bluetooth low energy (BLE) technology, also known as Bluetooth Smart, has gained popularity for IPS due to its low power consumption and wide availability and does not require LOS propagation. It uses proximity or RSS techniques to estimate the position of a target [9]. BLE technology operates on the 2.4 GHz ISM band and offers a range of up to 10 meters [20]. While similarly to ZigBee, it utilises a network of beacon nodes placed throughout the indoor environment, it differs from ZigBee since the Bluetooth standard is a proprietary format, and its gross bit rate is around 1 Mbps. Bluetooth requires a good number of relatively expensive receiving cells and that the target must host a microcontroller that supports Bluetooth radio. ZigBee is better suited for larger networks since it is more scalable and secure, but with trade-offs such as limited range and slower data transfer rate. On the other hand, Bluetooth is suitable for smaller networks and high-speed data transfers.

5.4 Wireless local area network (WLAN)

The IEEE 802.11 WLAN standard is a widely used technology for wireless communication in indoor environments. It provides a means of communication between devices using radio waves at a frequency of 2.4 GHz or 5 GHz and can support high-speed data transfer up to around 100 Mbps. The use of WLAN for indoor positioning is primarily based on the principle that the RSS of WLAN access points can be used to estimate the distance between a target and an access point [57] with a typical accuracy of 3 m to 30 m with an update rate of few seconds [20]. This information can then be used in combination with trilateration or fingerprinting techniques to determine the position of the device within the indoor space. On the other hand, AOA, TDOA, and TOA are more difficult to apply for WLAN IPS, due to the complexity of time delay and angular measurements [3]. An empirical model and a theoretical analysis on Wi-Fi-based indoor positioning and communication are presented in Ref. [12]. An algorithm that integrates indoor target positioning and communication based on Wi-Fi signals is reported to exploit the complexity and the high cost of developing the algorithm across more than one application. WLAN does not require LOS propagation, it is almost readily available in many built environments and most existing mobile devices are equipped with WLAN connectivity. WLAN IPS requires simple and low-cost equipment. The main disadvantage with using WLAN fingerprinting systems is the need to frequently recalculating the predefined RSS map. This is particularly true in dynamic environments with people or objects constantly moving around [57]. In addition, this technology provides a low accuracy and suffers from a lack of effective signal usage [12].

5.5 Ultra-wideband (UWB)

Ultra-wideband (UWB) is an emerging and promising IPS technology as reported in Ref. [11]. It offers several advantages over other technologies, such as high accuracy, precise ranging capabilities, and robustness in multipath environments. Due to its high performance, a common application for UWB is in indoor navigation aids for the visually impaired persons [4, 5]. UWB employs a communication channel that spreads information out over a wide portion of the frequency spectrum with a bandwidth greater than 500 MHz [3]. This allows UWB transmitters to transmit large amounts of data (up to 100 Mbps) while consuming low energy. The use of UWB technology for indoor positioning can be based on a wide range of signal estimation techniques including TOA, TDOA, AOA, RSS, and hybrid algorithms [11]. UWB has been found to provide accuracy in the range of tens of centimetres, making it one of the most accurate indoor positioning technologies available. Additionally, UWB can penetrate obstacles such as walls and objects, making it suitable for indoor environments, where LOS communication may not always be possible. If it is properly designed, UWB does not interfere with existing RF systems. The main disadvantages of UWB technology are the high cost of the equipment [3] and that signal interference can be caused by metallic and liquid materials present in the indoor environment [20].

5.6 Infrared (IR)

Infrared radiation can be used to transmit data between different devices [61]. It is typically used for short-range communication and requires LOS propagation.

Direct IR, such as Infrared Data Association (IrDA), uses point-to-point ad hoc data transmission for very low-power communication which reaches a maximum data rate of around 16 Mbps [9]. On the other hand, diffuse IR features stronger signals than direct IR; therefore, it has a longer range up to around 12 metres. Diffuse IR uses wide angle light emitting diodes (LED) that emit signals in many directions, allowing for one-to-many connections, and does not require direct LOS between devices [9]. The main advantage of IR technology is its ability to provide a secure communication, since IR signals cannot penetrate through walls, and thus, they cannot be easily intercepted or tampered with. This ensures the privacy and the security of data transmission. Disadvantages of direct IR technology are its limited range since it is easily blocked by obstacles and requires LOS communication, making it suitable only in small spaces [3]. On the other hand, diffuse IR systems suffer from a degraded performance in locations having fluorescent lighting or direct sunlight, which create interference even though the transmitted data is modulated. Proximity, TDOA, and AOA techniques are frequently used with this technology.

5.7 Visible light communication (VLC)

Visible light communication (VLC) is a short-range wireless technology, where the visible spectrum emitted by LED is modulated to transmit data at a very high data rate [10, 38]. Each LED emits a different encoded flicker which is specific for a particular location or area and can be coherently detected by a receiver, located on the target *via* a photodiode sensor. This IPS technology employs the readily available lighting infrastructure within a building, thus facilitating its deployment. VLC-based IPSs have the capability to provide a resolution in the centimetre range [10, 14]. A theoretical accuracy analysis on a VLC-based IPS using RSS was presented in Ref. [62]. VLC positioning can be used in RF sensitive areas such as hospitals. TDOA and RSS techniques are frequently used with this technology [38, 63]. While the simulation results presented in the literature are quite promising [62], experimental data show that VLC positioning has several challenges including inter-cell interference, multipath reflection, limited range, the need of LOS communication, and the reduction of the calculation time [14]. In addition, the localisation accuracy is dependent on the ambient light noise, time measurement, and the mobility of the target [14].

5.8 Image-based technology

Image-based technologies or optical methods utilise visual information from cameras or sensors to determine indoor positioning. These technologies often rely on computer vision algorithms to extract features from images and use them to estimate the position of a target [3]. Upon identifying these features, 3D maps are generated by comparing and mapping the captured images to a predefined set of reference images with known locations. Three dimensional maps create a highly detailed and searchable database of the environment. The database is then used by the system to determine the position and the orientation of the device, by using localisation algorithms which match the captured images to the visual cues in the database. The performance attained depends a lot on the type of camera or sensor used, the lighting conditions, and the extracted information obtained from the images [3]. Image-based technologies have gained increasing attention in the field of IPS since they are relatively cheaper when compared to UWB and ultrasonic technologies and are easily deployed [9]. Nonetheless, this technology requires LOS, and its coverage is generally restricted to one room or area [3].

These systems can be categorised into two main types: camera-based systems and sensor-based systems. Camera-based systems have been widely reported in literature [60, 64–66], where different types of cameras are used including smart phone cameras, omni-directional cameras, and 3D cameras. The movement of the camera, located on a target, with respect to a fixed scenario is often used to determine the target's location. On the other hand, sensor-based systems use static sensors such as depth sensors or laser rangefinders to capture the 3D information about the environment to locate moving targets [3].

5.9 Ultrasonic

Ultrasonic technology makes use of ultrasound waves, featuring a frequency above 20 kHz to estimate the relative distance between different objects. An ultrasonic transmitter emits ultrasonic waves into the surrounding environment, which propagates through the air or other media as a series of compressions and rarefactions [57]. While ultrasonic waves do not require LOS propagation conditions and do not interfere with electromagnetic waves, they may suffer from attenuation due to obstacles and are not able to efficiently penetrate solid walls. In fact, when ultrasonic waves encounter an object or surface, they are reflected towards the sensor, due to the difference in the acoustic impedance between the transmitting medium and the object. These systems employ TOA signal acquisition of ultrasonic pulses travelling from the emitters to the receivers. They can estimate the target's position through multilateration using three or more fixed receivers [67]. Ultrasonic positioning systems have a relatively short range, making them suitable only for certain indoor environments [9, 57]. This technology is not very efficient in terms of scalability, as the increase in number of simultaneous transceivers in an environment affects system performance due to increased interference [2].

5.10 Dead reckoning

Dead reckoning is a technique used to estimate the position of an object or a person *via* tracking, based on its previous position and the data obtained from inertial measurement sensors such as accelerometers, gyroscopes, and magnetometers. Since these sensors are readily available in mobile devices such as smart phones [68], dead reckoning is very cost effective as it requires no additional hardware or fingerprinting. The major issues with this technique are that inertial measurements provide position information relative to a known starting point [3] and the sensors used often suffer from drifting. This means that over time, the estimated position becomes less accurate as errors accumulate. Nonetheless, by frequently updating the absolute position, these errors can be contained within certain bounds [69]. In addition, with the use of sensor fusion, where inputs from multiple inertial sensors are integrated using techniques such as Kalman filtering [70], provides an improved accuracy and error reduction [71]. Dead reckoning can also be combined with other positioning technologies such as Wi-Fi, Bluetooth, and UWB to improve accuracy and reduce drift.

6. Future research directions

As IPS continues to evolve, there is a growing need for a robust infrastructure to support their operation. This includes the installation of access points, beacons, sensors, and other necessary hardware throughout indoor spaces to ensure comprehensive coverage and accurate positioning. Additionally, advancements in signal processing techniques, such as complex signal analysis and optimisation algorithms, have allowed for a more accurate and reliable indoor positioning. Many IPSs now use a combination of different technologies to enhance accuracy and reliability. Examples include combining Wi-Fi-based systems with Bluetooth low-energy or RFID technologies or integrating visual-based systems with sensor fusion approaches [72]. There are other promising future advancements and research directions on which to embark on. These developments are expected to further enhance the accuracy, reliability, and overall capabilities of indoor positioning technology. The following is a summary of several emerging trends in the field.

There is an increasing focus on developing indoor mapping and navigation solutions alongside IPS. These solutions provide users with detailed maps of indoor spaces and offer step-by-step navigation guidance, like GPS navigation in outdoor environments [9]. Another future advancement is the integration of AR technology [17]. By combining indoor positioning data with AR capabilities, users can experience enhanced LBS that provide interactive and immersive experiences within indoor environments. AR overlays can offer real-time information about nearby points of interest or interactive navigation guidance through visual cues and markers overlaid on the user's portable or wearable device [2, 73]. This seamless integration of AR and indoor positioning is anticipated to revolutionise various sectors, including retail, hospitality, and entertainment [73].

Future advancements in IPS may also focus on improving multi-user support. By developing systems that can accurately track and manage the locations of multiple users or objects simultaneously, indoor positioning technology can be applied to various collaborative and interactive applications. These include group navigation, location-based gaming, or indoor social networking platforms [57].

The synergy between IPS and the smart building infrastructure is an avenue for significant advancement. As smart buildings increasingly incorporate IoT devices, environmental sensors, and automation systems, the integration of indoor positioning technology can enable context-aware applications, person-alised environmental controls, and seamless interactions between occupants and the built environment. This convergence is projected to pave the way for truly intelligent and adaptive indoor spaces [17]. By integrating environmental sensors to detect factors such as air quality, temperature, or humidity, indoor positioning technology can provide users with valuable environmental data, thus going beyond the provision of location information. This expansion of functionality could support applications ranging from indoor environmental monitoring to personalised location-based recommendations based on environmental conditions [57].

In order to address growing concerns about data privacy and security, future IPSs are expected to implement advanced privacy-preserving techniques. This includes the use of secure and anonymised data collection methods, robust encryption mechanisms, and transparent user consent frameworks to ensure the responsible handling of location data. By prioritising privacy protection, IPS can earn greater trust and acceptance by the users and the regulatory bodies [9]. The ethical and legal implications of collecting and processing location data cannot be overlooked. Striking a balance between providing valuable LBS and respecting user privacy rights requires ongoing attention and adherence to the evolving regulatory frameworks and the industry best practices. Standardisation and interoperability remain crucial factors for the widespread adoption of IPS. As the industry continues to innovate and introduce new technologies, the establishment of standardised protocols and frameworks will facilitate seamless integration and interoperability between different IPSs, promoting a cohesive and efficient ecosystem for indoor LBS [17].

Another anticipated advancement is the integration of sensor fusion and edge computing in IPS [57]. Edge computing is an emerging technology that brings data processing and analysis closer to the source of data generation. This reduces latency and improves real-time decision-making [74]. By combining sensor fusion techniques with edge computing, IPS can take advantage of the power of a variety of sensors, such as accelerometers, gyroscopes, and magnetometers. By combining data from multiple sensors such as cameras, inertial measurement units, and wireless signals, IPS can achieve higher accuracy and robustness in challenging indoor environments. Additionally, the use of edge computing allows for real-time processing and analysis of sensor data, reducing latency and improving overall system responsiveness.

Machine learning algorithms are increasingly being used in IPS to improve accuracy and adaptability. These algorithms learn from the data collected from various sensors and devices, allowing the system to make informed and accurate location estimations [67]. The integration of artificial intelligence (AI) and predictive analytics into IPS represents a significant future direction. By employing AI algorithms and predictive analytics, IPS can also anticipate user movement patterns, predict crowd dynamics, and optimise resource allocation within indoor spaces. This predictive capability can lead to more efficient space utilisation, enhanced safety measures, and improved overall user experiences [75]. With the ongoing evolution of wireless communication technologies, the emergence of 6G networks is expected to revolutionise IPS [13, 76]. These networks promise ultra-low latency, high data rates, and seamless connectivity. These features will significantly enhance the real-time performance and the reliability of indoor positioning solutions [75]. This technological leap is expected to open new possibilities for immersive location-based experiences and advanced indoor navigation applications.

7. Conclusion

This chapter presented a comparative review of the state-of-the-art IPS. It aimed to contribute to the advancement of indoor positioning technology by providing a complete account on the currently available technologies and algorithms. The review encompassed a diverse range of technologies employed in IPS, including Wi-Fi-based systems, Bluetooth low-energy solutions, RFID technologies, UWB, and VLC amongst many others. In addition, the main types of signal acquisition and position estimation techniques used in IPS were discussed and compared. A focus on the evolution of LBS within confined spaces was also presented. The performance of an IPS is highly impacted by the selection of the technology, methodology, and algorithms. The comparative analysis delved into the practical implications of these systems, by considering factors such as design and deployment cost, accuracy, power efficiency, and adaptability to different indoor environments. An appropriate solution to attain specific attributes is strongly related to the given application. Indoor positioning remains an ongoing research field due to the challenges encountered in indoor environments and the necessity for greater accuracy. Hybrid positioning methods are promising for the future, as they seek to blend various approaches to enhance performance. While considerable progress was made in the recent years, there are still several open issues that need to be addressed including multi-user support, improving energy efficiency, cost reduction, signal coverage, data privacy and security, and full integration with IoT systems, amongst many others. In addition, this chapter offered valuable perspectives for future research directions and novel practical applications. The integration and adoption of technologies such as AR, edge computing and 6G mobile networks, is expected to provide a substantial advancement in IPS. These technologies are expected to enhance the accuracy, reliability, and overall performance of IPS. In addition, they will provide new applications and an improved user experience that goes beyond the provision of location information.

Dedication

To my beloved wife, Charmaine, whose unwavering love and support is my beacon through life's turbulent seas. Your presence is a constant source of joy and strength, and I am eternally grateful for the incredible journey we share together.

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