

Review of Indoor Positioning: Radio Wave Technology

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Abstract: The indoor positioning system (IPS) is becoming increasingly important in accurately determining the locations of objects by the utilization of micro-electro-mechanical-systems (MEMS) involving smartphone sensors, embedded sources, mapping localizations, and wireless communication networks. Generally, a global positioning system (GPS) may not be effective in servicing the reality of a complex indoor environment, due to the limitations of the line-of-sight (LoS) path from the satellite. Different techniques have been used in indoor localization services (ILSs) in order to solve particular issues, such as multipath environments, the energy inefficiency of long-term battery usage, intensive labour and the resources of offline information collection and the estimation of accumulated positioning errors. Moreover, advanced algorithms, machine learning, and valuable algorithms have given rise to effective ways in determining indoor locations. This paper presents a comprehensive review on the positioning algorithms for indoors, based on advances reported in radio wave, infrared, visible light, sound, and magnetic field technologies. The traditional ranging parameters in addition to advanced parameters such as channel state information (CSI), reference signal received power (RSRP), and reference signal received quality (RSRQ) are also presented for distance estimation in localization systems. In summary, the recent advanced algorithms can offer precise positioning behaviour for an unknown environment in indoor locations.

Keywords: indoor positioning; radio wave technologies; triangulation; fingerprinting; machine learning; ultrasonic sensor



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1. Introduction

With the increasing improvement of the Internet of Things (IoT), location-based services and localization-based computing have attracted much attention because of their widespread applications [1]. Hence, information on the locations of the targets plays an important role in localization systems [2]. Localization systems are used to locate or track people or devices, in developing existing systems, which can use different technologies and methods depending on the application. For instance, the estimation of outdoor positioning, tracking and navigation have been used by satellite system with Google Maps, which supports global coverage, such as GPS, assisted-global positioning system (AGPS), global navigation satellite systems (GNSS), assisted-global navigation satellite systems (AGNSS). All these systems provide their coordinates (latitude and longitude) from a satellite location parameter that estimates the desired target location obtained from other network resources. Among them, GPS is one of the most well-known and universal technologies for outdoor localization systems used in vehicle navigation and missile guidance.

Indoor location positioning systems can develop the service areas provided by smart homes, warehouses, museums, healthcare centres, indoor parking lots, and shopping

malls. For that reason, it is attractive to research on a low-cost design that can provide accurate localization in the indoor surroundings. However, indoor localization has more challenges than outdoor localization. By the consideration of extra information, the ray tracing techniques are widely used for increasing indoor radio wave propagation in the wireless communication system [3]. The authors described 3D smart ray tracing approach by varying frequency values such as at 4.5, 28 and at 38 GHz. which are compared with former methods, targeting to improve accuracy and efficiency [4–9].

Indeed, the pattern of signals in indoor environments is more complicated than outdoor environments due to the multipath effect, fading, reflecting, deep shadowing effect and the deterioration of delay resulting from pervasive hindrances and interactive interference [10,11]. Therefore, the common GPS-based localization system is difficult for indoor localization systems because of the dependence on the line-of-sight (LoS) communication of radio signals. Additionally, indoor localization systems need a much higher precision than the meter-level solution of outdoor localization [12]. As GPS signals are met with challenges in indoor localization systems, many researchers have proposed a variety of technologies such as infrared, visible light, sound (audible and ultrasound) magnetic field, an inertial navigation system (INS), computer vision-based and radio frequency to achieve indoor localization.

Among these technologies of short and medium-range communication, infrared (IR) and visible light are included in the seven-segment of the electromagnetic spectrum. Infrared technology and visible light exist under the optical technology of electromagnetic radiation. The tracking and positioning of the user are described based on light beams [13] in which infrared transmitters are mounted on the room corner and the user is engaged with an infrared receiver. The drawback of IR technology is that it cannot easily pass through the making room with strong materials for LoS environment. Furthermore, it required hardware components to tag on the human body. In [14], the authors exploited passive infrared indoor localization methods through thermal radiation due to the formation of motion body, instead of using a hardware tag as a connection device. In the visible spectrum, the human eye can see the electro-magnetic waves as a white light that is a combination of the rainbow colours. Fluorescent lamps and light-emitting diodes (LEDs) are used to transmit signals as a visible light communication (VLC) which includes a short-range optical wireless communication of indoor appliances. The transmission data can be obtained via light beams as the light pulses and these receiving data change with distance. The authors in [15] performed a comprehensive survey of VLC innovation by applying LED light bulbs. VLC has been intended to replace the usage of other radio frequency areas, as a more efficient and commercially orientated high bandwidth transmission but requires higher hardware complexity [16]. For computer vision and image processing, adequate illumination from the light source can support the camera to detect the location of things successfully. Consequently, the camera-based location determinations are dependent on the lighting condition.

Sound technologies (ultra- or audible sound) have constraints within the 20 Hz to 20 kHz range of audio frequency. Human ears are able to absorb acoustic intensity in environments. A microphone or speaker could be used to generate the electrical signals converted from sound signals through transducers. Sound detection sensors, microphone sensors and ultrasonic sensors are commercially used to detect the intensity of sound. Subsequently, an ultrasonic sensor is used as a distance sensor by first estimating the time taken in traveling the sound signal between the source and sensor. Echo and trigger pins of ultrasonic sensor work as a transmitter and receiver during this work. Therefore, for indoor tracking purposes, an ultrasonic sensor is used as a distance-based device in an ultrasonic location detection system [17]. Signal-based distance measurement techniques, time of arrival (TOA) and time difference on arrival (TDOA) can be used to measure time for distance estimation. However, ultrasound signals cannot penetrate well through an obstruction. Thus, it is inappropriate for sensing in wide-ranging locations; hence, sound technology is not prevalent in indoor localization appliances.

In recent times, modern smartphones are composed of compatible sensors for specialty functions. Smartphone sensors are capable of collecting data based on the relative human motion by means of the estimated position is provided by the embedded sensors. More precisely, an accelerometer, gyroscope, proximity sensor, magnetometer, and pedometer inside a mobile phone are viable for the tracking and navigation system. Considering for indoor positioning system, magnetic field measurement and an inertial navigation system could determine the location problem in the coverage area. A magnetic field (inertial technology) uses the magnetometer to measure the magnetic field variations as well as to support the position estimation of a person or object. Magnetic field data are used for pedestrian dead reckoning (PDR) application [18,19]. In [18], the system is integrated into the long period operation and coarse indoor ambience that is based on the walking prolongation of approximately 1390 m and the operating time 45 min. However, the magnetic positioning system (MPS) is not intended for accuracy. In [19], the author proposed the positioning and calibration algorithms of indoor MPS and then the impressive positioning accuracy computed in a real indoor environment. An argument in favour of magnetic signatures is that it can infiltrate extensively in obstructed materials and can operate the endeavours of non-line-of sight (NLoS) propagation. INS is a navigation device, typically used for manned and unmanned aerial vehicles, underwater vehicles and mobile robot applications. MEMS have low-cost sensors and inertial measurement units (IMUs) sensors that can help capture the human movement direction and angular speed. This brings the positioning solution of PDR that the multiplicity of smartphone built-in sensors can detect the footstep length counting, the speed of human movements and rotation. It is also a GPS aided device [20,21]. The frequent criticism of smartphone built-in sensors is that the motion estimated errors and time-invariant process have occurred in a comparative study of radio signal attractiveness.

Radio frequency technologies based on an indoor positioning system (IPS) are widely used. It is based on the signal strength technologies, especially for wireless communication devices, and uses narrow-band with spread-spectrum signals. Radio waves are generated by the electromagnetic field of sources or devices. Useful localization technologies in IPS are radio frequency technologies involving wireless communication technologies, which define the physical and medium access control (MAC) layer of open system interconnection (OSI) model—Bluetooth, radio frequency identification (RFID), ZigBee, ultra-wide band (UWB), wireless local area network (WLAN), and mobile network. Two groups of indoor localization systems are used, namely active localization and passive localization [22]. RFID [23–28], UWB [29–31], Bluetooth [32–34], ZigBee [35–38], IR [15,17,39], ultrasonic [40–42], hybrid systems and the standard of the Institution of Electrical and Electronic Engineering (IEEE) 802.11 WLANs [42] are included in active IPS, in which the person is attached to the tag or device to enable locating the position in a dynamic indoor localization framework. If the person does not carry any tag or device alongside with the trajectory in the location area, then it is defined as a passive indoor localization. Device-free passive localization such as that in [43–45], UWB [46–48], physical contact, computer vision and differential air are categorized as passive indoor localization.

Furthermore, the location determination scheme mainly involves distance estimations and position calculations. Distance estimation is usually mentioned as ranging, and is based on different traditional parameters such as the received signal strength (RSS), angle of arrival (AOA), TOA, and TDOA of beacon signal changes between the target node and the beacon nodes. The accuracy of positioning is reliant on the signal parameters, particularly on the wireless technology used, as it defines the value of the approximation of the signal parameters [31]. Therefore, several researchers have studied other parameters including round trip time (RTT), direction of arrival (DOA), channel state information (CSI), reference signal received power (RSRP), and reference signal received quality (RSRQ). On the other hand, a number of positioning methods have been investigated, such as triangulation, trilateration, proximity methods, and the advanced positioning algorithms, such as fingerprinting or pattern recognition, PDR, machining learning, and deep learning, all to

precisely locate people or devices in localization systems. In addition, hybrid algorithms were also proposed for indoor localization approaches since each method has its own advantages and limitations [49].

For existing works, an author conducted a survey of support technologies for network localization systems [50]. Indoor localization parameters and technologies were reviewed in [4,51]. The author overviewed smartphones based on indoor positioning schemes [52]. Indoor positioning based on Wi-Fi fingerprint localization was compared in [53]. The survey described parameter comparisons relying on distinct indoor technologies. The localization techniques for indoor scenarios are TOA or time of flight (TOF), TDOA, round trip time of flight (RTOF), AOA, phase of arrival (POA), received signal strength indicator (RSSI), and CSI. Then, preferable positioning approaches or positioning techniques have been developed in IPS, which are proximity estimation, triangulation estimation, trilateration estimation and pattern recognition or fingerprinting.

There are many techniques for accurate indoor positioning based on signal strength measurements. The technologies for indoor location and tracking have led to calculating the user's location which is based on an entire range localization such as building, room or limited spaces. Some issues are currently encountered as the main problem of indoor location because of the multipath signal and NLoS of signal in a given area. In this paper, we summarized the methods based on radio signal technologies which is extracted from the several existing papers of IPS.

This paper is organized as follows. Section 2 explains positioning parameters. Then, radio signal-based positioning is described in Section 3. Section 4 presents the positioning methods. Finally, Section 5 concludes this review on indoor positioning.

2. Parameter Based Positioning

This section presents measurement parameters for localization systems. Several parameters are utilized to determine the target position for indoor localization systems. The fundamental wireless signal measuring theorems in indoor positioning systems are RSSI, TOA, and AOA or DOA. In addition, TDOA, RTT, angle difference of arrival (ADOA), phase difference of arrival (PDOA), POA, CSI, RSRP, and RSRQ are also used in indoor positioning and tracking environments. This section will survey some signal measurements.

Table 1 shows the advantages and disadvantages of signal measurement parameters. Figure 1 depicts the distance-based and direction-based signal measurement parameters for indoor positioning systems.

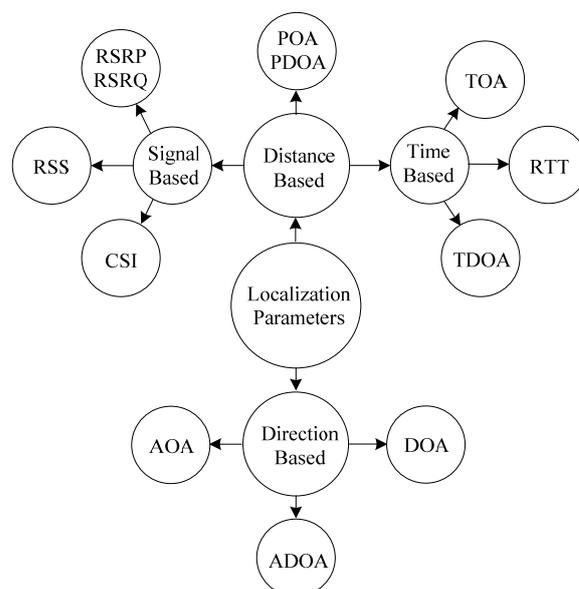


Figure 1. Localization system parameters for distance and direction measurement.

Table 1. Summary of the different localization measurement parameters.

Parameters	Advantages	Disadvantages
RSS	No need for time synchronization and angle measurement. Easy to implement. No need for extra hardware device. Eliminates energy consumption.	Prone to the noise, multipath effects and NLoS. Needs a fingerprinting database for scene analysis methods.
TOA	No need for any fingerprinting database. Provides high localization accuracy.	Needs time synchronization. Influences multipath and additive noise. Needs extra hardware device. Difficult to implement in narrow bandwidth.
TDOA	No need for any fingerprinting database. Does not require time synchronization among the device and received nodes.	Needs extra hardware devices. Difficult to implement in narrow bandwidth. Requires time synchronization among the received nodes.
RTT	No need for clock synchronization between the nodes. Reduces complexity, enhances reliability. High range measurement and update rate. Apply for passive RFID with proper synchronization.	Suffers multipath effects. Different processing time delays. Phase noise affects the accurate clock speed. No simultaneous response to large requests.
AOA	No time synchronization between measuring units. Provides high accuracy.	Needs an antenna array. Requires extra hardware. Influences multipath, NLoS, and additive noise.
DOA	Highly influenced by multipath effects.	Accuracy relies on accurate angle measurement.
ADOA	No need for any fingerprinting database. No need the information of angles in the variance between two AOA values.	Requires extra sensors like gyroscopes.
POA	Easy to obtain the signal's phase change during the propagation. Improves the accuracy integrated with RSSI, TOF, and TDOA.	Has an infinite number of path lengths. Requires LoS for high accuracy. Phase ambiguity issue due to phase wrapping.
PDOA	High accuracy. Reduces multipath effects.	Ambiguities in the distance estimation. Accuracy depends on multipath effect.
CSI	Provides more fine-grained signal characteristic information. Good stability and higher accuracy than RSS.	Needs labour-intensive site survey to calibrate. Does not need to be appropriate for most situations. Needs larger storage and more operation time.
RSRP RSRQ	Supports greater power information. Reduces proneness to local disturbances in the environment.	Impacts station interference and thermal noise.

2.1. RSSI

The received signal strength indicator (RSSI) is a comparative measurement of the RSS which has random units and is commonly described by a single chip vendor [51]. RSSI is a commonly used metric to find an estimation of the distance between a target and the node without resorting to complicated calculations. It computes distance by power loss, the signal strength deficiency, between two nodes. Figure 2 shows the RSSI-based trilateration method. This method can work using only a couple of nodes to obtain a distance estimation [54]. The RSSI-based algorithm only requires the received signal

strength and does not require an auxiliary hardware apparatus and time synchronization, able to achieve higher accuracy than other methods.

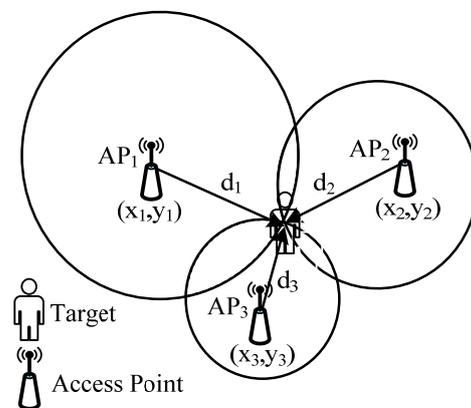


Figure 2. RSSI-based trilateration.

The RSSI technique can be classified into a range-based and range-free approach. The first approach is an RSSI based on a path loss model. The propagation model involves building a map associated with the physical regulations of the wireless signal. The precision and flexibility of the environment are poorer in the range-based method, which can locate the position of the object by using trilateration, min–max, and maximum likelihood algorithms. The latter approach generates the use of a fingerprinting database (radio map) for localization [55]. A range-free method does not require angle or distance measurements among nodes. The fingerprinting technique is higher in accuracy and can be used for various indoor environments. However, RSSI measurement can cause an error due to environmental effects. The real indoor environment consists of multiple obstacles that affect radio signal propagation [1].

RSSI is susceptible to noise and multipath effects which significantly decreases its localization accuracy [56]. In addition, there is the LoS problem between the two nodes, which can significantly influence error. However, RSSI calculation accuracy is increased by calibrating and analysing the radio signal propagation.

2.2. TOA

TOA is also known as TOF [28] and is described as the first period within which the signal reaches the receiver. It can estimate the distance to the node by computing the broadcast time travel of a wireless radio signal [57,58] as shown in Figure 3. The traditional TOA schemes needs a minimum of two or three reference nodes in a LoS situation with a target, to support a high level of position accuracy [59]. The nodes can be synchronized or the miss-synchronization in TOA and the signal must consist of the timestamp data [60]. To solve these issues, the TDOA method, as well as the round trip time of arrival (RTOA) method, also called RTOF, is implemented. RTOA ranging mechanisms are identical to TOA, but it does not need a corporate time reference within nodes. TOA is influenced by multipath and additive noise. Additive noise imitates the precision of the signal arrival time. This problem can be fixed by applying the TDOA instead of TOA [61].

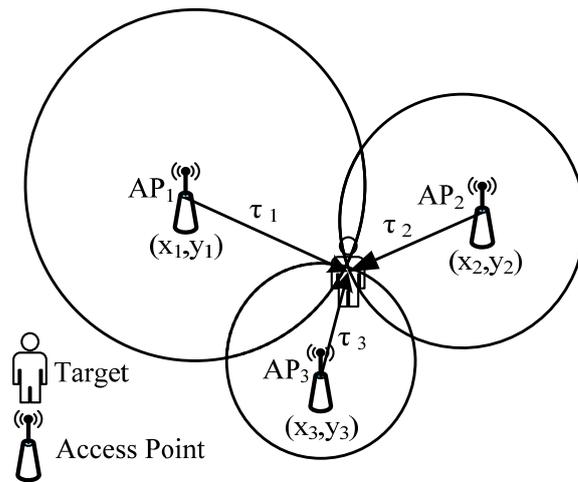


Figure 3. TOA-based trilateration.

2.3. TDOA

It is a technique to calculate the distance information between the two nodes. TDOA determines the variance of arriving times (timestamps) between the anchor nodes in the same package from the target. Figure 4 illustrates its basic operation for the TDOA-based method. This method requires at least three anchor nodes with known coordinates to find the object position. The anchor nodes listen to transmissions from the target and compute a position estimated by comparing the variances in the arrival times [62]. This method performs by determining the change in the time between a couple of anchor nodes.

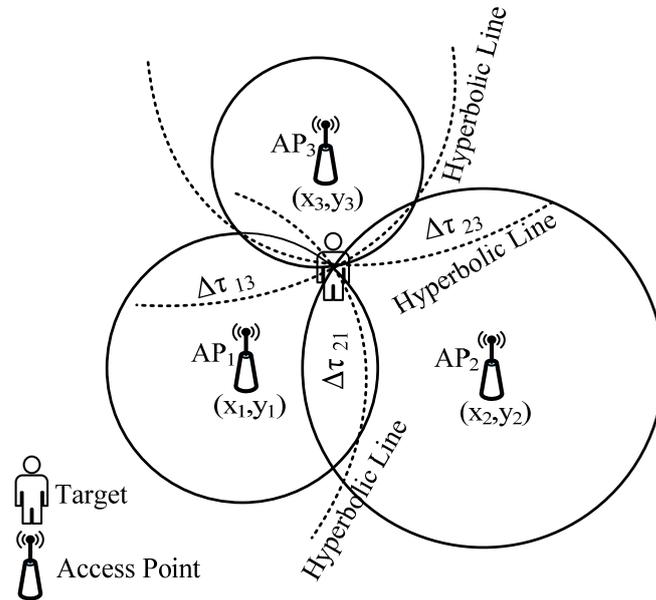


Figure 4. TDOA-based trilateration.

On the other hand, the multi-signal needs two different types of signals that have varying propagation speeds to compute its distance to another node. The accuracy of TDOA is due to complex indoor propagation such as multipath transmission and shadowing. The radio signals reaching the receiving antenna by different paths cause multipath transmission. This method needs extra equipment. The ultrasound or audible frequency can be used in this method using the same algorithm [61]. The achievement of the TDOA is subject to synchronization between the anchor nodes and the precision of the taken timestamp.

2.4. RTT

Wi-Fi-based two-way ranging approaches have been proposed for indoor positioning and tracking systems to improve the positioning accuracy. These positioning systems are based on fine time measurement (FTM) of the RTT of a signal between a smartphone (target) and an access point. The RTT or RTOF technique estimates the distance by the broadcast timestamp of the FTM message and the response of its acknowledgement [63] in Figure 5. This measurement approach is based on the TOF and develops to solve the synchronization problem subjected to the use of TOA. The RTT measurement does not need the clock synchronization between the nodes. This means less complexity and high reliability. In addition, the ranging error and range between a couple of devices are nearly independent when the clock operates at the same rate on the nodes. The FTM can give a large range estimation and a large update rate compared to the scene analysis system. However, the RTT ranging measurement has limitations with respect to its reflection, fading, shadowing, and unstable clock speed due to phase noise as well as a different processing time delay. Moreover, the FTM protocol has a concurrent processing capacity problem and an access point cannot concurrently reply to higher amounts of FTM inquiries [64].

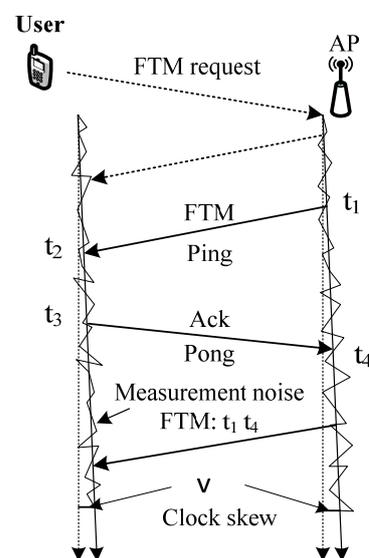


Figure 5. RTT with a skewed clock.

One approach is the Wi-Fi RTT-based indoor positioning system in car parks [65]. The proposed system used a trilateration method and a probabilistic method to estimate the car's location. The result of this system shows that the Wi-Fi RTT is suitable for industrial indoor positioning in a dynamic environment. This system achieves an average accuracy of 2.33 m and the accuracy can be improved with higher radio communication or a larger number of access points. Another approach is a hybrid algorithm based on the RTT and RSS, which was exploited to solve the restrictions of the Wi-Fi RTT ranging technique [64].

This approach presents the RTT estimation with a clock skew and investigates the RTT range error distribution. It also removes the RTT ranging offset at the emitter end by using the calibration method. The proposed system achieves scalability and accuracy in static and dynamic experiments in both the outside and inside environment. The average location accuracy of this work is 1.435 m and an update rate is 0.19 s in a real environment. Although the RTT-based indoor positioning system can achieve standard deviations of 1–2 m, in some applications, for example, an emergency worker in a multi-story building, this can impact the position error due to the signal bandwidth, the delay of the signal, and the noise gain. Therefore, the frequency diversity method was introduced for the accurate position estimation using weighted averages of evaluations with uncorrelated errors acquired in various networks [66].

2.5. AOA and ADOA

AOA is a technique of determining the position of objects by taking the angular data of that object with respect to the orientation of the receivers. A simple AOA calculation is to work on an antenna array on one sensor node. The angle-based method needs a minimum of three reference nodes coordinated to determine the position of the object by using a triangulation method as shown in Figure 6 [67]. In general, the AOA method can obtain angle data using radio array techniques and can estimate by using directional or multiple antennas. In multiple antennas, this acts by analysing the phase or time variation between the signals at different array items that have seen locations regarding the centre element.

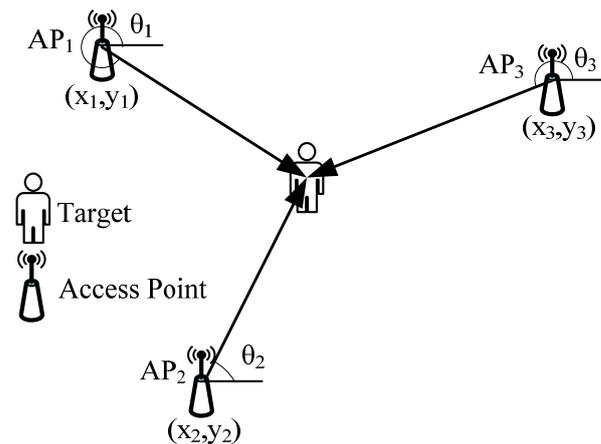


Figure 6. AOA-based triangulation.

In directional antennas, it acts by computing the RSSI ratio between many directional antennas that are carefully located to have a similarity between their major beams [61,68]. AOA determinations with the support of exact antenna design or hardware apparatus are utilized for inferring the location of the receiver. The improved complexity and the hardware necessity are the major interferences for the extensive success of AOA-based location systems [69]. AOA is also disturbed by noise, NLoS and the multipath. Moreover, the defects of LoS can be more serious than those of TDOA- or RSS-based techniques [70]. AOA needs additional space to offer spatial diversity and extra hardware that is a real waste of power, but it does not require time synchronization between nodes [71]. Both TOA and AOA parameters require reference units that can decide the arrival time and angle of the received signal which is unattainable to common WLAN devices. Thus, the RSSI technique is most extensively used in an indoor localization, positioning and tracking system. ADOA does not need the information on angles as it can be ignored in the variance between two AOA values. This means that the receivers are to be located towards a definite angle. AOA-based optical indoor positioning systems are more challenging due to the necessity to identify the orientation of the receiver. The optical receiver is either limited to certain orientations or it must be combined with gyroscopes and accelerometers to define its exact orientation. To solve this problem, ADOA is used for an optical indoor positioning system [72]. Hence, the ADOA does not require extra sensors like gyroscopes [69,73].

2.6. DOA

DOA-based measurements use the angle information of the received signal to estimate its position [74]. The DOA approach, also called AOA, is simpler than time-based measurements because of the estimation of the 2D position with only two angle measurements. The DOA-based positioning system is the evaluation of the signal AOA. The accuracy of the DOA-based localization system is highly impactful with regard to multipath effects. However, this technique depends on accurate angle measurements. The DOA estimation can be done by using an antenna array or direction. In addition, DOA-based systems have proposed and applied for a localization system integrating with different measurement

techniques such as RSS, TOF, TDOA, and RTOF. There are several different antenna implementations such as the narrowband system, switch beam, phase antenna array, and UWB-based system estimate localization based on DOA algorithms [75]. The DOA-based localization systems need a suitable antenna with different requirements.

DOA-based techniques are divided into the offline and online technique based on the applications [74]. In offline method, this computes multiple times, and the average value label as the fingerprints. By using these fingerprints, the triangulation method estimates the location. The offline systems have larger complexity and can be utilized for offline applications. In online method, the angles are determined from the received signals and the triangulation method estimates the position. These methods have smaller complexity and utilize real time applications. The DOA techniques have been presented for an indoor localization system to estimate channel characteristics and focus on the multipath propagation interference problem [76,77]. Moreover, a hybrid joint direction and time difference of arrival (JDTDOA) approach has introduced the precision of the system performance [78].

2.7. POA and PDOA

POA ranging techniques estimate the distance by measuring the phase of the carrier signal [51]. It is also called received signal phase (RSP). There is a number of POA measurements that have been used in RFID-based localization systems. The POA-based approach was introduced to increase accuracy and decrease disturbances due to multipath propagation in passive RFID 2D localization system [79]. The results of the estimated POA existed in an unlimited number of paths due to the 2π uncertainty in phase estimations. By means of the frequency-stepped continuous-waveform principle, the distance of the propagation path can compute definitely for a high bandwidth system. The POA techniques can be used integrated with different techniques such as TOF, TDOA, and RSSI to increase their performance. However, POA-based approaches may need LoS for high accuracy.

The ranging measurement based on PDOA uses the phase difference of the propagation path between the anchor nodes or the reader to the tag to calculate its distance [80]. It is also mostly used in RFID and wireless sensor networks (WSNs) system. The phase errors can be small due to the very small signal bandwidth. Unfortunately, unavoidable ambiguities can occur during the evaluation of the true distance due to the multipath effects and a 2π phase periodicity [81].

2.8. CSI

With new technology developments in wireless communication systems, 4G long-term evolution (LTE) mobile transmissions, and Wi-Fi systems have used orthogonal frequency division multiplexing (OFDM). OFDM converts information on several altered subcarriers at one band. In the IEEE 802.11 standard, the receiver wants to approximate CSI in the physical (PHY) layer for the data translation. The CSI is the channel frequency response of each subcarrier under the OFDM system within the frequency field. Thus, CSI utilizes dozens of times more data than traditional RSSI in the network features between the sender and the receiver [82]. In the frequency field, CSI is definitely the PHY layer data with a fine-grained characteristic value that defines the amplitude and phase of a single subcarrier [83]. In the field of narrowband transmissions, this denotes the network property of the transmission link that expresses the reduction in the signal in the development of communication between the two nodes, containing scattering, distance and environmental attenuation, as well as other information [84]. The CSI-based method uses the physical layer channel state information of a communication link. A corresponding CSI can be measured when a target is displayed indoors. The CSI fingerprint matching, triangulation, and trilateration method can be used to determine the location of the target [85,86].

The CSI-based method shows good stability and can achieve higher location accuracy than the RSSI-based method [51,87]. Moreover, CSI is favoured more than RSSI, since it develops the frequency diversity of Wi-Fi networks and is not coarse-grained like RSSI.

The CSI-based approach has many advantages such as the ease of arrangement given the pervasiveness of a Wi-Fi setup [88]. In addition, the CSI-based Wi-Fi localization system can achieve decimetre-level accuracy. On the other hand, CSI-based Wi-Fi schemes need a labour-intensive site survey to calibrate the access points (APs) location and the antenna array direction, which obstructs real-world implementation [89]. Another disadvantage is that the CSI-based fingerprinting method needs larger space and more comprehensive time due to a larger measurement of CSI compared with RSSI, which is not appropriate for most situations [82,90].

2.9. RSRP and RSRQ

The RSRP and RSRQ parameters are physical layer data from the 4G cellular system that are used to reasonably forecast the user position [91]. The RSRP computation is based on RSSI. It calculates mean obtainable strength by cell-specific reference signals [92]. Thus, it can afford greater signal strength information associated with various positions contrasting normal RSSI. The PHY layer RSRP reduces local disturbances in the surroundings. In the office location, the RSSI estimates from 4G towers produce a better forecast than RSSI signals from 2G towers, due to the existence of small cells.

The RSRQ parameter that delivers the value of received signals within the object device is developed from the RSSI and RSRP value. RSRQ is influenced by adjacent station interference and thermal noise and thus, when only RSRQ is utilized, achieves less precision than RSRP estimates. On the other hand, the accuracy of the RSRQ-based system is better than that by the RSRP signals when RSRQ values are used together with RSRP values [91].

3. Radio Signals-Based Positioning

This section describes radio and non-radio-based systems for IPS, depicted in Figure 7. A GPS that receives signals from satellites is broadly used and very popular in outdoor localization applications, but it is ineffective for indoor localization due to the LoS transmission problem. Therefore, various wireless technologies such as infrared, optical (LED, laser), ultrasound, an IMU, vision, VLC, and the radio signals—including Wi-Fi, ZigBee, Cellular, Sigfox, RFID, LoRa, NFC, Bluetooth, UWB, long-range radio (LoRa), sigfox, near field communication (NFC) and cellular networks—have been used in IPS. In addition, some of the works have been utilized in hybrid approaches for indoor positioning and tracking. This paper will discuss only the radio signal technologies. Table 2 provides the strengths and weaknesses of the radio technologies for indoor positioning systems.

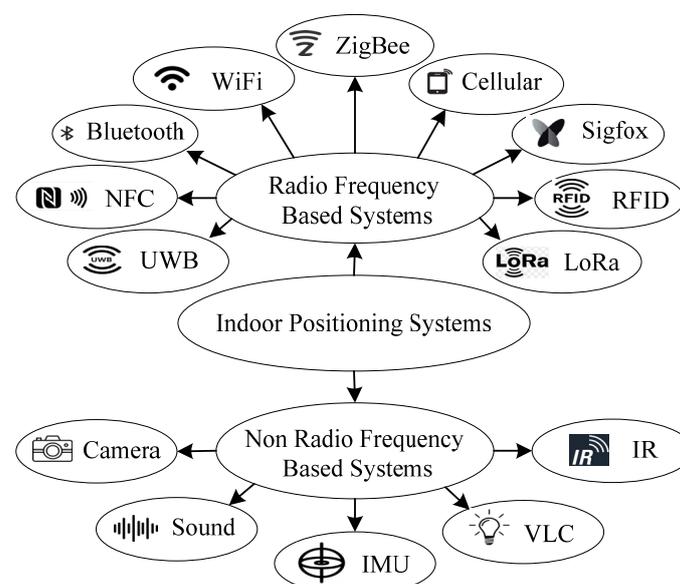


Figure 7. Categorization of indoor positioning technologies.

Table 2. Summary of radio-based technologies for indoor positioning.

Technologies	Parameters	Advantages	Disadvantages
Wi-Fi	RSS/AOA TDOA/TOA RTT/CSI	Moderate power (216.71 mW on average). No extra hardware. Easy deployment. Cover large regions.	Affects time-varying RSS. Difficult to finish the task of building a smart city. Accuracy depends on the amount of access points.
Bluetooth	RSS/TOA TDOA AOA/TOF	Low power (0.367 mW on average). Easy deployment. Has a much higher data rate than ZigBee.	Needs extra hardware. Affect time-varying RSS. Interferes with same frequency band. Accuracy depends on its access point. Has a much shorter range than ZigBee.
RFID	RSS/TOA DOA/AOA TDOA PDOA	No contact and NLoS nature. Simultaneous and fast reading of multiple tag. Resilience to environmental changes. Reduce sensitivity regarding user orientation.	Needs extra hardware. Multipath effect and signal fluctuation. Large error with more target tags to locate. Limited capabilities of the passive tags.
ZigBee	RSS/TOA TDOA/AOA	Lower power (17.68 mW on average). No require much network bandwidth. Has higher latencies	Needs extra hardware. Interference and strength of signals. Difficult to create a connection with the smart phone.
UWB	AOA/TOA TDOA RSS/DOA	High accuracy. Unaffected by interference. Fewer effects on humans. Suitable for body-centric and wearable network.	Short range, high cost. Challenges in NLoS. Needs extra hardware. Provides high accuracy.
NFC	RSS	Low cost, high accuracy. Provides secure and private navigation.	Accuracy depends on the number and proper placement of tags.
LoRa	RSS TOA TDOA	Long range. Extremely low energy. Covers large area.	Signal attenuation and multipath. Long-range between server and device. Operate outdoor-to-indoor
SigFox	RSS TOA	Long range, covers large area. Serves larger active nodes. Very low energy.	Long-range between server and device. Operate outdoor-to-indoor signal attenuation.
Cellular 1G/2G/3G 4G/5G Long-term evolution (LTE)	TOA/CSI TDOA/RSS RSRP/RSRQ	Long-range. High accuracy. No extra cost.	Requires synchronized based stations.
Hybrid	RSS /TDOA RSRQ/RSRP PDOA/TOA AOA/DOA	Improve the performance. Overcome the limitations. Better than pure algorithm solution. Reduces system complexity.	Not enough information with single network

3.1. Wi-Fi Technology

Wi-Fi, which is a wireless local area network (WLAN), is a well known technology in broadband communications, specifically for machine-to-machine schemes and human communication [93]. The Wireless Ethernet IEEE 802.11 (Wi-Fi) devices generally transmit over 2.4 GHz, nevertheless, now 5 GHz is extensively being utilized for transmission due to less interference, less noise, higher constant connection, and enhanced speed [94]. The Wi-Fi network is available through mobile devices such as laptops, tablets, mobile phones and others in consequence of an active saleable off-the-self simple infrastructure for an IPS [95,96]. Wi-Fi signal is used to focus the problem of indoor positioning and tracking, due to the ubiquitous placement of Wi-Fi access points, low cost over other indoor wireless technologies, low energy consumption, and without additional hardware requirements [35,97]. Several algorithms and ranging parameters have been presented to increase Wi-Fi-based IPS; however, most of the algorithms and measurement solutions need large computing properties and specific hardware [98]. Wi-Fi localization algorithms are introduced, including an AOA-based algorithm (triangulation) [99], trilateration algorithm [1,100], RSSI-based fingerprinting algorithm [101,102] and CSI-based fingerprinting algorithm [98,103].

Among the algorithms, the fingerprinting algorithm and the trilateration algorithm are often employed in Wi-Fi-based indoor localization. However, fingerprinting localization algorithms give the best performance and attract the researcher's attention due to easy implementation, low complexity, no need for the LoS measurements of APs and specialized hardware [104]. The average localization errors are described as 2~3 m in Wi-Fi-based positioning algorithms [92]. Wireless signals of Wi-Fi access points can protect huge areas, however, they need multipart hardware and software collaboration with each other [38]. In addition, Wi-Fi-based positioning implementation can be extremely affected by environmental effects such as the geography of the barrier, people's mobility or crowdedness, and weather [92]. The multipath failing of Wi-Fi signals affects the time-varying RSSI of signals that influence the precision of the Wi-Fi location. Furthermore, Wi-Fi scanning time, around 3~4 s in common smartphones, gives the low quality of its services in the context of a refreshment time [92].

3.2. Bluetooth Technology

Bluetooth low energy (BLE) is mostly supported by smart devices today. It is based on the Institute of Electrical and Electronics Engineers (IEEE) 802.15 standard. The Bluetooth 4.0 protocol was distributed and it was announced in 2010 [105]. BLE signal is a kind of electromagnetic signal that works in the range from 2.4 GHz to 2.4835 GHz band in Industrial Scientific and Medical (ISM) [106]. In 2013, a new iBeacon technology was presented by Apple Inc. The iBeacon technology was created based on BLE technology that can send directly with smartphones and it is has lower power and a lower cost than conventional Bluetooth and Wi-Fi technologies [107–110]. In addition, the launch of Google's Eddystone™ open standard in 2015 produced new and better broadcast formats that have aided in the development of interest in the widespread use and embedding of Bluetooth beacon platforms [32].

BLE is designed with very short ranged wireless transmissions. Hence, the estimated errors using Wi-Fi-based systems are normally much higher than those in BLE-based systems [111]. The sensing length of Bluetooth is at most 10 m, with great power cost and is only ideal for a small space [38]. Bluetooth devices are varied because of different productions, rated voltage, and energy, and therefore, the RSS can change as much as 20 dBm [112]. Moreover, in reality, Bluetooth broadcast power takes time-varying characteristics [108].

Although the Bluetooth-based system needs further hardware devices in contrast with the Wi-Fi-based system, it can attain accuracies in the range of 1.2 m [97]. In addition, low power Bluetooth is chosen in indoor positioning systems and IoT applications because of advantages such as low cost, low power (0.367 mW average power consumption) [107], small size and easy deployment [34,113–116]. It can be as extended as much as 100 m by

adjusting the broadcast power, which creates the possibility of a wider range of indoor positioning using Bluetooth 4.0 [117]. The Bluetooth-based indoor location system mainly use proximity detection, trilateration, and fingerprinting. However, the positioning accuracy will be affected by the stability of the Bluetooth node and the indoor propagating environment. Several experiments with the Bluetooth scheme show that accurate positioning needs additional exploration [105]. Furthermore, Bluetooth technology obstructs Wi-Fi for the reason that they share the same frequency band [92].

3.3. ZigBee Technology

The ZigBee technology is a short-range wireless communication technology, based on the IEEE 802.15.4 standard as its medium access control (MAC) layer and physical layer (PHY) standard. It operates at the 2.4 GHz frequency with a lower bit rate. ZigBee can be applied with a star, tree networks, and mesh networks by relating to a microcontroller [118–120]. The ZigBee design classifies three types of devices such as the ZigBee coordinator, ZigBee Router, and ZigBee End Device that combines ZigBee radios. A ZigBee End Device is cheaper to produce than a ZigBee coordinator or ZigBee Router [54].

ZigBee devices can control their own data and prevent some data damage by using carrier-sense multiple access/collision avoidance (CSMA/CA). ZigBee devices are defined by aspects, for instance, of energy detection and link characteristics that permit RSS measurements to be simply resolved. ZigBee technology has a wider range than BLE technology, as such it is able to communicate further by using a mesh network of relay nodes to arrive at a destination [107]. The ZigBee-based localization system used to link quality indication (LQI) instead of the RSSI [121]. The ZigBee standard-based wireless technology has many advantages such as its low cost, low power (17.68 mW average power consumption) [107], safety, reliability, robustness, and low data rates. In addition to its light weight, it has low-bandwidth and a faster computation processing. [122–124].

The ZigBee technology was commonly used to measure indoor positioning and tracking previously because of its advantages [35,36,119,121]. Conversely, ZigBee-based positioning impacts accuracy because of the interference and strength of the signals [38]. ZigBee positioning also has a definite constraint on positioning in real time when using RSSI, due to the short-range and great latency shortcoming of 802.15.4 wireless technology [117]. Furthermore, it requires extra hardware and is not a trend among current IoT users. The low power features of ZigBee technology have not happened because of its limitations in data transmissions. This network usually allows a device to succeed in its data transmission over almost 100 m despite its low powered characteristics. In the network, each node can connect directly with other nodes or through neighbouring nodes in the network [125,126].

3.4. RFID Technology

RFID is a wireless non-contact technology that obtains automatic identification by transmitting data from an RFID tag to the reader through an electromagnetic signal. Generally, RFID technology consists of a reader, tags, and a computer [2,26]. RFID technologies are based on an active tag technology [28,127] and passive tag technology [25,124,128,129]. Active tags have a larger detecting range using high power consumption and higher cost, although the passive tags are appropriate for short distance static point location, and only applicable for a small space [38]. However, RFID passive tags are more common than active RFID tags in localization systems. Furthermore, RFID technologies achieved high improvement in the tracking of assets, warehousing, management, logistics, car inventory, personnel location, and robot navigation. Its advantages are a high read range, rapid read speed, low price, suitability for large-scale deployments, high security, battery-free tags, and scalability [2,26]. Moreover, RFID technology is widely used in industries other than in laser scanners, cameras, or ultrasound technology [27]. However, the localization approach based on RFID can easily be changed by the random moving objects in the domain, due to the multipath effect and signal fluctuation that reduce its accuracy. Moreover, due to

diffraction, reflection, and NLoS, RFID signal transmissions are complex in an indoor environment. In addition, RFID signals collected from the real-time environment are noisy [24].

In many applications, the position identification of objects is also of extreme importance. Thus, the RFID technology-based localization has been analysed extensively. The RFID-based conventional localization systems usually use the characteristics of radio signals such as the signal strength, travel time, and direction. In RFID-based indoor localization systems, the triangulation methods, zone or building level solutions, and LANDMARC, a location sensing prototype methods, are usually developed to locate a target [130]. For the RFID-based ultra-high frequency position scheme, the power signals received by the readers have to be computed in the RSSI-based IPS. The RSSI based methods contain the referenced tag-based methods and distance-based methods. The distance-based algorithms create signal propagation models such as the free-space path-loss model, logarithmic distance model, and logarithmic normal distribution model for the signal power reduction and the signal propagation distance [131].

Furthermore, location tracking based on the RFID system can be divided into reader tracking and tag tracking [127]. In the RFID tag tracking, the target to be located is connected with an RFID tag. The RFID reader is positioned in the surroundings. When the target steps into the surroundings, the RFID reader stores the information. The RFID reader can either send the information to a centralized server, which computes the location, or collaborate with each other to compute the location by themselves. Then, the location outcome is returned to the target. In the reader tracking, each object to be localized brings in a reader in addition to an antenna integrated with the reader. The tags are installed in the surroundings. A reader acquires the information and estimates its position. Reader tracking decreases setup costs by using inexpensive tags [27]. The RFID reader positioning is also vital for RFID large-scale implementation. Therefore, the RFID reader positioning was investigated to develop a higher accurate positioning and tracking system for the indoor environment, and to improve the tracking performance that can be used for various active and passive RFID standards [132,133].

3.5. UWB Technology

UWB is an attractive technology in wireless sensor networks, which allows for very high data rates over a short distance because of its wide bandwidth. This broad bandwidth also involves a high temporal resolution, enabling a higher accuracy, and hence more accurate positioning of each target device in the network [134]. The IEEE 802.15.4a (UWB) wireless communication technologies are quickly developing and they will be in the 5G technology [29]. UWB transmission is described by its capacity to communicate short pulses with low-power spectral density in a high-frequency range, from 3.1 to 10.6 GHz. UWB wireless technology is an innovative technology for greater resolution in indoor positioning and tracking applications, such as in healthcare, medical facilities, construction sites, and sports [31,135,136]. Moreover, due to the nature of large bandwidth, UWB signals offer greater protection against interference. In addition, it has less impact on the human body due to the short-transmission power [71,137].

Localization based on UWB concentrates on the trilateration and angulation methods [29,68,138–141] on the unknown location of a target device using three or more beacon nodes. Range-based approaches such as TOA and TDOA have good accuracy and are most suited for localization and ranging for wireless networks because of the large bandwidth of UWB signals [57]. However, RSS is hardly utilized in UWB-based positioning systems, since distance calculation is less accurate compared with using the TOA, TDOA, and AOA-based method [142]. UWB technology has many advantages, including the protection of multipath intrusion, large data rate, convenience, low power consumption, and suitable for wearable networks and body-centric applications [57,71,143]. The UWB technologies are mostly focused on non-line-of-sight (NLoS) modifications [134,140]. It is able to offer centimetre and sub-metre accuracy for position measurement in an indoor localization

system [31,144]. However, an ultra-wideband-based positioning system has many challenges for high-accuracy applications in buildings, which includes sampling rate limits, device synchronization, human-body shadowing effects, antenna phase-axis variation, and multipath interference. There are many reasons for a millimetre or sub-millimetre accuracy [138,139]. To make the higher range accuracy, the UWB-based positioning technologies require complex infrastructure and high cost [145].

3.6. Cellular Technology

Cellular wireless signals such as 2G, 3G, 4G, and 5G (millimetre wave technology) have been used for localization systems [69,92,146–151]. Also, the cellular implementations aim to give effective coverage in the indoor environment. Specifically, the new LTE signals have a large bandwidth, a structure and a synchronization frame that can create them, which are well matched for location determinations [152]. In 4G LTE web systems, the RSRP and RSRQ values are used to observe the signal strength. The RSRP is termed and received as a signal indicator. The RSRP and RSRQ are defined in the 3rd Generation Partnership Project (3GPP) typical design [92,153]. Normally, 3GPP LTE divides between the frequency division duplexing mode and the time-division duplexing mode. The time-division duplexing mode uses the same frequency while the frequency division duplexing mode uses two dissimilar frequency ranges for uplink and downlink.

The LTE downlink physical layer is constructed in accordance with the OFDM modulation. The LTE signal-based positioning systems consider a number of aspects. These signals should rather occur within the downlink with no operator demand, thus no precise operation of the system is required, preventing further cost and system traffic. The LTE signal would be excluded for a base position, therefore the signals from various base positions working on a similar frequency range can be divided. Furthermore, the bandwidth of the communicated signal would be exploited in the network bandwidth to give a frequency impulse response with better resolution [152].

The radio signal scatterings for base stations on various radio channels change with positions. Thus, a radio channel combination can support escape from misclassification instead of depending on one radio channel. In addition, the cellular signals are obtained by smartphones without extra cost. Furthermore, coarse location data can be obtained from cellular networks, although its precision is lacking for most indoor applications. Moreover, 2G cellular signals only apply averaged RSSI that is less crude, as it consists of power associating with thermal noise, serving cells, and co-channel cells [91]. The propagation channel actually disturbs the accuracy of an LTE-based localization system, which is unsuitable for location approximation in a distributed antenna system (DAS) [154]. Moreover, the LTE commercial systems are not developed for TDOA-based positioning system due to the non-compromise of positioning reference signals (PRS) and non-synchronized base stations [155].

4. Positioning Algorithms

A localization system can classify the positioning and variable aspects, which involve signal strength, propagation time, received angle, ranging and devices. The position estimation techniques can be applied to define location coordinates. The traditional positioning algorithms are proximity and triangulation. The fingerprinting method, PDR method, and hybrid methods are also adopted to estimate the user position in the indoor system. There are several positioning algorithms described in the previous works. The positioning algorithms are illustrated in Figure 8.

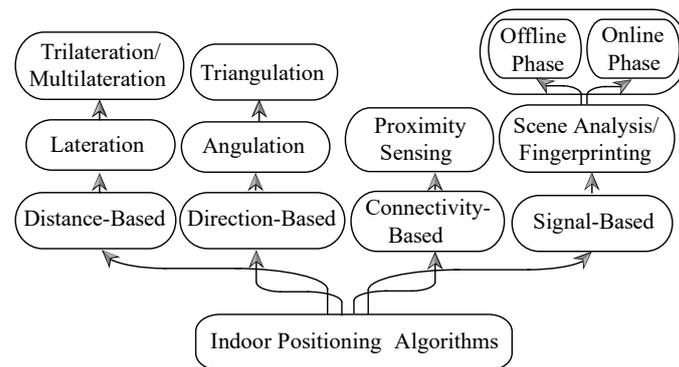


Figure 8. Description of the overall indoor positioning algorithms.

Among these methods, the most popular were presented. As the present review is related to the positioning algorithms or approaches that detect the optimal positioning accuracy of a target within indoor environments, the localization technologies in Section 2 and parameter-based measurement methods in Section 3 were combined with these algorithms at that point for finding the position and the direction of a target object.

4.1. Proximity Algorithm

Proximity estimation is the simplest technique to implement for localization systems. In [50,156], the proximity technique estimates the target position when the target is close to a known position, as shown in Figure 9. It is a detection or range-free-based method that does not calculate the exact position coordinates of the object. Therefore, proximity estimation is a coarse-grained technique [157]. The proximity method was used in global system for a mobile communication (GSM)-based localization system. It succeeds in achieving an accuracy between 50 and 200 m, which depends on the GSM cell size [158]. The method needs a compact deployment of BLE beacons to obtain the highest precision but does not need a calibration process for localization [159]. The proximity method has a high variance which sometimes might not satisfy the need for localization. Thus, this method is not as widely used as the previous works.

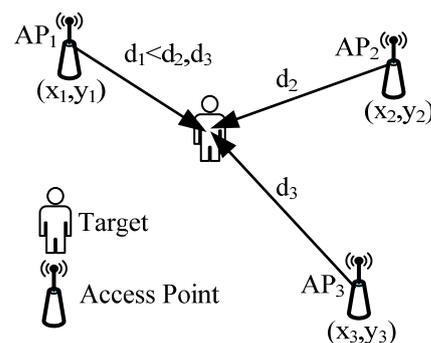


Figure 9. Proximity-based positioning method.

4.2. Triangulation Algorithm

Triangulation is a range-based localization method, which includes angulation (triangulation) and lateration (trilateration). Lateration is a distance-based method and angulation is an angle-based method. In the lateration method, TOA, TDOA, and RSS are involved. Angulation methods include, such as AOA, and ADOA. Triangulation estimation techniques are used to compute the relative location of a user by determining distances, using a geometrical property of triangles, and is called a fine-gained technique. This technique uses the point of overlap shaped by three circles of reference points to define the position. Basically, it provides a range of localization based on known distances. The distances are estimated by using different signal measurement procedures such as RSS, time-based

technology (such as TOA, RTT, and TDOA), and angle-based AOA [1]. The triangulation method is more adjustable, such as the system estimates' location in the actual environment and the system is capable of contending with the distinct environmental variations [160]. The trilateration method is a different fingerprinting method so it does not need an offline phase. Conversely, this method needs the relevant coordinate position of reference points (RPs) and its MAC address collected in a central database [161]. Although trilateration is able to produce accurate locations, it is actually sensitive to the precision and accuracy of the distance estimations [162]. Moreover, the triangulation technique needs an adjustment feature to decrease the signal attenuation produced by the barriers and human body intrusions that can affect the localization precision [160].

4.3. Multilateration Algorithm

The multilateration method is an extension of the triangulation method with more than three reference points in estimating a target location [156,163]. Radio frequency multilateration method estimates the location of the target using the strength of signals received from many non-collocated and non-collinear transmitters [164]. In the multilateration method, the localization accuracy highly depends on the distance measurement between a target device and an access point. The multilateration-based localization methods are used in the domain of an information-oriented construction site for simply realizing ad hoc wireless locating networks [165]. A true-range multilateration method is also utilized for a bidirectional target tracking and navigation system [142]. Although time-based multilateration localization techniques are chosen for the positioning of wideband signals, these techniques are not so insignificant with narrowband signals such as GSM. The time-based process challenges are due to the needs of synchronization precision and timestamp determination, both in the nanoseconds range [62]. Furthermore, the radio frequency fingerprinting method gives better results than the radio frequency multilateration method, even though the radio frequency multilateration method gives less of an error rate and enhanced solution for small spaces [164].

Multilateration is the most common method for deriving a position. From the estimated distances and known positions of the anchors, the following system of equations can be derived [131,162]:

$$\begin{aligned}(x_1 - x)^2 + (y_1 - y)^2 &= d_1^2, \\ &\vdots \\ (x_n - x)^2 + (y_n - y)^2 &= d_n^2.\end{aligned}\tag{1}$$

where the unknown position is denoted by (x, y) . The system can be linearized by subtracting the last equation from the first $n - 1$ equations:

$$\begin{aligned}x_1^2 - x_n^2 - 2(x_1 - x_n)x + y_1^2 - y_n^2 \\ - 2(y_1 - y_n)y &= d_1^2 - d_n^2, \\ &\vdots \\ x_{n-1}^2 - x_n^2 - 2(x_{n-1} - x_n)x + y_{n-1}^2 \\ - y_n^2 - 2(y_{n-1} - y_n)y &= d_{n-1}^2 - d_n^2.\end{aligned}\tag{2}$$

Reordering the terms gives a proper system of linear equations in the form $Ax = b$, where:

$$A = \begin{bmatrix} 2(x_1 - x_n) & 2(y_1 - y_n) \\ \vdots & \vdots \\ 2(x_{n-1} - x_n) & 2(y_{n-1} - y_n) \end{bmatrix}, b = \begin{bmatrix} x_1^2 - x_n^2 + y_1^2 - y_n^2 + d_n^2 - d_1^2 \\ \vdots \\ x_{n-1}^2 - x_n^2 + y_{n-1}^2 - y_n^2 + d_n^2 - d_{n-1}^2 \end{bmatrix}.\tag{3}$$

The system is solved using a standard least-squares approach:

$$\hat{x} = (A^T A)^{-1} A^T b.\tag{4}$$

The symbol \hat{x} expresses the estimated location.

4.4. Min–Max Algorithm

The min–max method is used as a positioning technique in the range-based localization. The idea of the min–max algorithm is to make a box area or square for each anchor node using its location and calculated distance. Then, the overlap of these squares is determined. The location of the node is put in the centre of the overlap box. That is to say, each anchor node determines the RSSI rate from the object node and computes its distance to an object node using the RSSI rate based on the radio propagation model. Then, a square with two times the measured distance is sketched over the anchor node [162]. The object node is situated within the intersecting area of the squares sketched around all anchor nodes. The min–max algorithm is focused on 3D and 2D indoor localization [166,167]. The method can be easily implemented because it essentially consists of a small number of additions, subtractions and logical comparisons [168]. Min–max supports a coarse location approximation, and can give a high location error in some situations, such as when a bounding box is used instead of a circle, providing a broader region measured from each anchor [162]. Moreover, the weighted centroid localization estimation has the same manner as the min–max algorithm [169]. Therefore, an extended min–max method was proposed to increase the precision of the min–max method containing more operations [168]. The min–max method for a node with distance estimates to three anchors are illustrated in Figure 10.

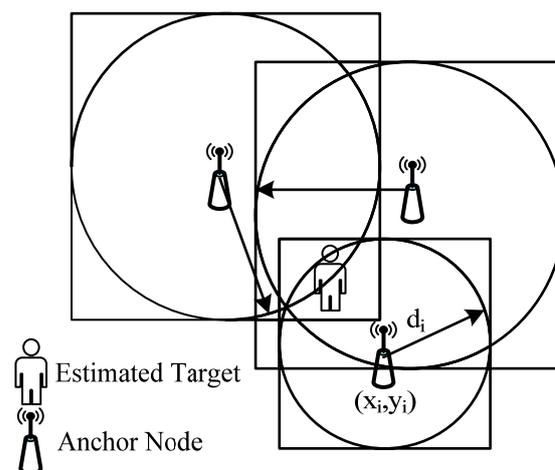


Figure 10. Min–max-based positioning method.

The bounding box of anchor a is created by adding and subtracting the estimated distance d_a from the anchor position (x_a, y_a) :

$$[x_a - d_a, y_a - d_a] \times [x_a + d_a, y_a + d_a]. \quad (5)$$

The intersection of the bounding boxes is computed by taking the maximum of all coordinate minimums and the minimum of all maximums:

$$[\max(x_i - d_i), \max(y_i - d_i)] \times [\min(x_i + d_i), \min(y_i + d_i)]. \quad (6)$$

The final position is set to the average of both corner coordinates [162,170].

4.5. Maximum Likelihood Algorithm

The maximum likelihood method is based on the traditional statistical inference principle [171]. This method guesses the location of the target node by minimizing the variance of estimated distance error as shown in Figure 11. This approximation can be

implemented using a minimum mean square error (MMSE) standard. However, the performance of this method is unstable considering the quantity of anchor nodes [172].

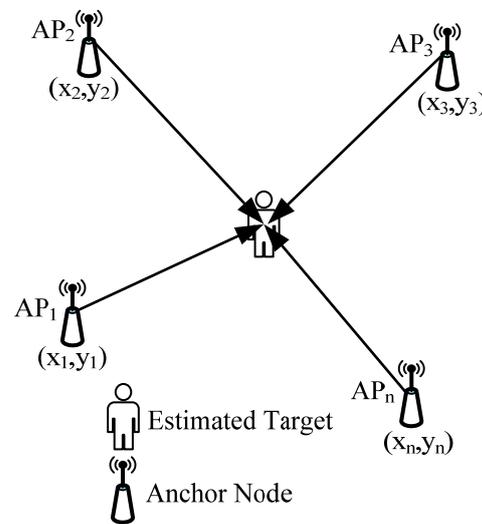


Figure 11. Maximum likelihood-based positioning method.

A maximum likelihood algorithm is a probabilistic search method. These methods normally make more precise positioning as contrasted with the deterministic method because the deterministic method cannot adjust well to the signal variation. [173–175].

In the following, a description for a maximum likelihood algorithm based on RSSI is presented [170]. First, an estimate of distance d_i to each reference device is derived from the RSSI value. Then, the node defines the error e_i between the measured and the actual distance, given by

$$e_i(x_0, y_0) = d_i - \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2} \tag{7}$$

In Equation (7), $b = (x_0, y_0)$ is the unknown position of the target node, and (x_i, y_i) the position of the i -th reference node. This algorithm estimates the target’s position by minimizing e_i . The unknown node position estimate b calculated with MMSE estimation is the solution of:

$$y = Xb. \tag{8}$$

$$X = \begin{bmatrix} 2(x_k - x_1) & 2(y_k - y_1) \\ \vdots & \vdots \\ 2(x_k - x_{k-1}) & 2(y_k - y_{k-1}) \end{bmatrix}, y = \begin{bmatrix} -x_1^2 - y_1^2 + d_1^2 - (x_k^2 - y_k^2 + d_k^2) \\ \vdots \\ -x_{k-1}^2 - y_{k-1}^2 + d_{k-1}^2 - (x_k^2 - y_k^2 + d_k^2) \end{bmatrix}. \tag{9}$$

The coordinates (x_0, y_0) can be computed by

$$b = (X^T X)^{-1} X^T y. \tag{10}$$

The detailed mathematical derivations can be found in [171].

4.6. Fingerprinting Localization Algorithm

In IPS and indoor location-based services, the fingerprinting (FP) localization method is a prevalent method to attempt the optimizing of position accuracy using range-free information in building structures, for example, in shopping malls, convenience shops, market places, offices, hospitals, airports, factories, industries, campus buildings and smart buildings. To solve the difficulties in IPS, the FP localization algorithm has the ability to obtain high positioning accuracy, reducing the hardware complexity and undesirable influence of the multipath effect, better than range-based methods.

The fingerprinting method is normally formulated in two phases, the offline phase (training) and online phase (testing). The basic operation of this method is as shown in Figure 12.

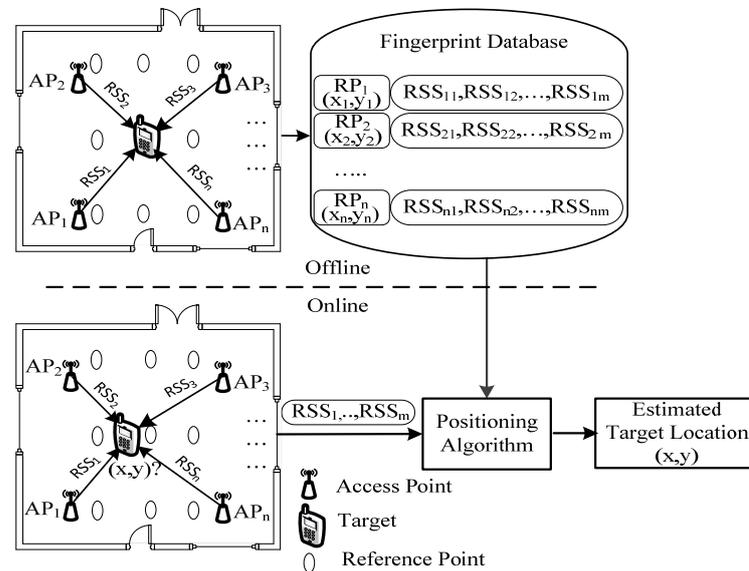


Figure 12. Fingerprinting-based positioning method.

In the offline phase, the spatial-temporal RSS data from each AP location are gathered and saved in the database as current location coordinates, called RPs. Moreover, the database of previously known patterns received from a known Wi-Fi base is collected by uniformly selecting RSS measurements for each point as an FP. In the online phase, the mobile device or receiver accepts the new RSS measurements from different APs. Then, the comparison and recognition processes are performed between the measured RSS values and reference FPs for position estimations.

An FP localization technique brings new challenges that the primarily fingerprints database should be accurate for the requirement of good performance and desired positioning accuracy [176]. An FP method could find the target's position by utilizing RSSI measurements that come from various transmitters or different network sources. Many different APs' location diminish the positioning accuracy due to RSS noise and attenuation. RSSI works in MAC which is known as the datalink's sublayer in the OSI model, which is the available wireless network interface controllers by access points (APs). In the MAC layer, a radio map can build itself by using the signal strength of APs which is known through offline processing. Especially, wireless-based positioning, and RSSI measurements, are stored in the database and matching between the information of stored data and the current target position of the RSSI radio map measurements. Thus, the time consumption and labour-intensive aspects take part as essential issues to construct the radio map for collecting data [176–178]. In addition, RSSI FP localization are commonly applied; it is cost effective and relieves the complexity of additional hardware for an indoor positioning system. According to the indoor environment, the complexity and the estimation of performance methods are considered by the implementation of the Wi-Fi deployment stage. The relative strength of the known Wi-Fi-based stage is used to address the accurate position as well as the propagation model of a known antenna is used to predict the distance by the signal propagation of time-based methods, such as triangulation [179], trilateration [1,161,162] and multilateration [63,164]. However, the conventional time-based method is not sufficient for the RSS ranging aspect of indoor performance.

Generally, the FP based on radio maps can be divided into deterministic and probabilistic approaches. Deterministic and probabilistic approaches are utilized for measurements of indoor positioning using RSSI [179–187], as shown in Figure 13.

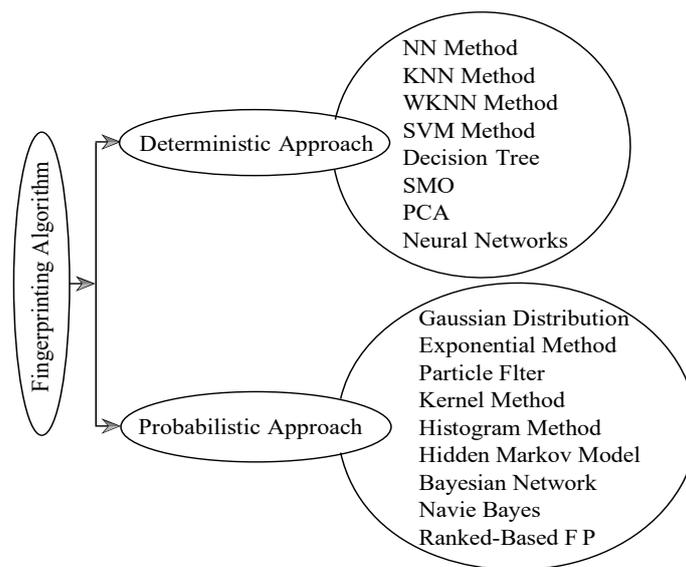


Figure 13. Illustration of the fingerprinting algorithm.

The deterministic approach is based on the fixed values of known variables; it only takes certain variable values without the consideration of uncertain random variables. Indeed, a deterministic algorithm is finding the optimization of similarity between the new measurements of online data and the dataset of FPs offline. In [179], the RADAR system is concerned with the deterministic location approach, and proved competent to determine the user's location with the nearest neighbour of Euclidian distance by using scalar values. The classification method of nearest neighbour (NN), K-nearest neighbour (KNN), and weighted K-nearest neighbour (WKNN) are implemented for the matching of nearest locations in the online phase [187]. These mathematical equations are able to compute the mobile device's actual position. In addition to this, the support vector machine (SVM) is used as an advanced deterministic approach for the WLAN standard which can also give better accuracy on type location [188].

The probabilistic approach is based on the conditional probability distribution function (PDF) of unknown variables by providing more accurate results with statistical framework [184]. It can guess the position of dimension between reference points (RPs) of FP and target measurement depending on the statistical conditions [189]. In [180], the Horus WLAN system can perform the location determination with high accuracy and low computation by using a probabilistic approach in order to improve the RADAR system. Then, the authors in [184] described the increased accuracy of about more than 64% by implementing with a linear autoregressive model in a Horus WLAN system in which the process uses the correlation of sequential sample values received from the same APs. In the Horus system, the Bayesian model is applied to obtain the probability distribution of random variables by addressing the noisy signal strength characteristics in wireless networks [180,190,191]. In [192], the authors introduce batteries of sufficient energy with a probabilistic fingerprinting method on the application of a heterogeneous mobile device platform. This approach is able to solve the energy inefficiency of a smartphone due to the long time consumption of collection and the computation of the measurement data from apps, as well as increasing the smartphone battery lifetime. The probabilistic FP approach is not similar to the conventional one, as it extends the battery lifetime without a deterioration in its position accuracy.

As a whole, the deterministic method can estimate the user's position by using the classical time-based methods and angle-based methods like TOA, TDOA and AOA. A deterministic method can deduce the probability of the user's position more closely within a little distance. The probabilistic method can decrease the noisy characteristic of random signals received. In spite of the probabilistic method requiring more information, it can

estimate the location more precisely than the deterministic method, for example, where the object is located presently. However, the low capacity of integrated electronic devices such as sensors and track tags are not effective for the probabilistic approach as these devices do not have a suitable ability for computing purposes.

4.7. Radio Map Construction Aiding the Offline Workload

Apparently, crowdsourcing, simultaneous localization and mapping (SLAM) and the path loss model enable creating the radio map construction within a specific time. These methods could reduce the human workload and the depletion time, and prior map information. The radio map is basically important for indoor localization to handle the collected RSS measurement from pre-labelled RPs. The heterogeneous smartphones have already built-in various sensors bases that are typically workable for acquiring data types, tracking the users' motion, orientation, acceleration, direction, pressures and step counts. However, it cannot be perfect in the case of collecting the spread of RSS values from the whole large building in practical applications.

The crowdsourcing method is entitled as an eminent scheme of an automatically constructed radio map by reducing the major IPS issues, intensively, the time and human workforce. Tables 3 and 4 describe the location accuracy and performance comparison of calibration and human effortlessness. The collection of (RSS) information needs to be updated quickly by user phones and to remain for a certain distance and time, because crowdsource data are normally inaccurate. However, the mobile crowdsourcing idea is becoming an attractive way to construct the radio map without pre-labelled reference points and manual calibration [193,194]. Crowdsourcing data can be received from the updated fingerprinting RSSI information in a database which is provided by the IMU sensor and PDR trajectory. Then, the radio map is automatically constructed at the indoor location [195–197]. Most of the wireless indoor locations are regarded as a continuous structure independent on the environment changes. The authors in [198] effectively solved the calibration process and maintenance process due to the changing state in the environment. Additionally, associated with crowdsourcing Wi-Fi, the authors in [199] also presented a way to execute three aspects, which are manual calibration-free, reduced measurement time and the preservation of FP values at each location. In [194], Wi-Fi-based IPS crowdsourcing presents the solution to secure consideration for interrupting attacks and intend to obtain the trusty and authentic data submission between RSS fingerprints of neighbouring positions. Indeed, creating a radio map is locally intended to address the laborious problem and the disturbance of numerous RSS measurements. In this case, crowdsourcing could reduce the labour-intensiveness, the overpowering time for map construction and is obstructively used for the estimation of RSS without deduction power [195,200].

Table 3. The summary of the indoor positioning algorithm.

Algorithms	Usage Information	Measurement	Pros and Cons
Proximity (range-free information)	Cell origin results	Limited coverage, connectivity-based	High variances. Inaccurate and unsatisfactory in positioning. Coarse-grained results.
Trilateration (range-based information)	Geometric properties	Timing information, distance-based	Ineffective for nonlinear model. Fined-grained results.
Multilateration (range-based information)	Geometric properties	Timing information, distance-based	Ineffective for nonlinear model. Fined-grained results.
Triangulation (range-based information)	Geometric properties	Incident angle, direction-based	Ineffective for nonlinear model. Fined-grained results.
Fingerprinting (range-free information)	Statistical and empirical analysis	Signal strength intensity, signal-based	Accurate high positioning. Reduce apparatus complexity. Mitigate operation and human power. Effective linear and nonlinear models. Easy upgrade information to amend. Challenges for dynamically environmental changes.

Table 4. Comparison of location accuracy based on crowdsourcing.

Paper	Evaluation	Data Type	Infrastructure	Performance
[193]	LiFS, automatic FPs calibration	Wi-Fi/accelerometer sensors.	Entirety office building. Cover range 1600 m ² , Total of 26 rooms.	5.88 m (average error) Error 80% under 9 m Error 60% under 6 m (small and room error)
[198]	Unsupervised learning Manual calibration effortless.	Wi-Fi	Office building, (length 80 m and width 32 m) floor plan.	Around 3 m
[199]	FreeLoc, Handle complexity calibration of users and devices robust and consistent localization performance	Wi-Fi	University building.	Heterogeneity devices error (around 2 and 4 m)
[200]	Extracting effective RSS from crowdsource data RSS changing information from multiple trajectory	Wi-Fi/ IMU data	Office building, floor area 4600 m ² and corridor area 411 m ² .	Positioning accuracy 1.5 m
[197]	RCILS. Semantic graph and activity sequence, mitigates RSS variance due to device heterogeneity and environmental changes condition.	Wi-Fi/accelerometer/ compass gyroscope and barometer.	Office building, 2756.25 m ² floor plan.	Medium error 1.6 m

Another option to consider for radio map construction is SLAM. SLAM derives from the mapping of mobile robot trajectory in which the robot explores the map in free space autonomously. By implementing it in IPS, SLAM incorporates smartphones sensors types. Especially the Wi-Fi signal, Bluetooth RSS, IMU data, odometry data, magnetic data, and compass data could be used to exploit the location estimation, as summarized in Table 5. Wi-Fi SLAM uses only Wi-Fi RSS with Gaussian distribution, Gaussian process latent variable model (GP-LVM) [201]. During the training phase, the training data can collect without pre-defined coordinates in Wi-Fi SLAM. GP-LVM could convert these high-dimensional RSS measurements from different APs to a two-latent dimensional space (x-y coordinates of the user's device). In an affluent signal environment, RSS constraints generally occur as a similar signal strength information cause of nearby locations in the environment. The location of these signal strengths was observed in the reading collected by a person freedom walk at the whole building. In fact, Wi-Fi-SLAM could be satisfied with the corresponding localization accuracy of unlabelled training data, a mean localization error with 3.97 ± 0.95 m. Wi-Fi GraphSLAM uses Wi-Fi RSS from 536 APs, pedometry and gyroscope data [202]. Unlike Wi-Fi-SLAM using GP-LVM, the specific predefined maps are not essential in GraphSLAM problem. Obviously, GraphSLAM can reduce the complexity and limitations. The localization accuracy is between 1.75 and 2.18 m. However, it uses the smartphone IMU sensors to track a walking user in which pedometry data could not reliably obtain the accurate step length of a person. FootSLAM uses only the odometric data from a foot-mounted inertial sensor based on the Bayesian framework estimation [203,204]. FootSLAM is constructed as the probabilistic map with a hexagon grid in the 2D area where the data are recorded by a person walking through the building. It is implemented by using a Rao-Blackwellized particle filter (RBPF) to follow the user's trajectory and relative map. Alternatively, PlaceSLAM uses proximity information, and can improve FootSLAM accuracy [204,205]. WiSLAM uses odometric data from the foot-mounted sensor and Wi-Fi RSS, which comes from the idea of using of FootSLAM and PlaceSLAM. The WiSLAM solution improves the FootSLAM convergence based on the probabilistic Bayesian network [204]. The SignalSLAM uses Wi-Fi and Bluetooth RSS, 4G LTE RSRP, magnetic data, GPS reference points and NFC tag for constructing an automatic generated radio map [148]. Although SignalSLAM is extended, so is the adaptation of the Wi-Fi GraphSLAM Technique [202]. An objection to GraphSLAM is that the measured signal similarity is computed in a single space underlying the data collected of a user walking speed from 5 to 10 s. This refers to the measured signals from many different Aps, which are practically unremarkable between time segments. A unique feature of SLAM is to build up an unknown environment and be able to estimate optimal landmark location and nonlinearity. This could find an unknown location existing in an unknown environment and it can continuously build a successful map resulting in accurate indoor tracking [206]. The SLAM algorithm is also considered for real-time in map-building application [207]. The positive aspect of SLAM is that it has the ability to tackle map management [208], from multipath-assisted to upgraded location accuracy and tracking. Based on radio frequency or acoustic signal, the multipath delay is considered in order to obtain a continuous connection between indoor localization and mapping infrastructure [209]. To implement WLAN infrastructure, SLAM based on Wi-Fi FP is capable of setting up an indoor topological map, by using a sensor-based platform [139,210,211]. In addition, SLAM based on the magnetic field, namely, magnetic SLAM, can be used to promote the indoor localization accuracy using a weighted particle filter.

Table 5. The comparison of the location accuracy based on simultaneous localization and mapping (SLAM).

Paper	Evaluation	Data Type	Infrastructure	Performance
[201]	Wi-FiSLAM GP-LVM (special constraint and unlabelled map information)	Wi-Fi	University building, floor level 250 m to a half of km	Mean localization error 3.97 ± 0.95 m
[202]	Wi-Fi GraphSLAM unnecessary special constraint and labelled data, addressing runtime complexity	Wi-Fi/pedometry and gyroscope	University building, cover 600 m^2 , 1.2 km radius	Localization accuracy range 1.75 m to 2.8 m, mean error 2.23 ± 1.25 m
[203]	FootSLAM approach to track user's step and location based on odometry(track motion)	Foot mounted IMU sensors	Building/ constraint area	Pedestrian's relative location accuracy, 1 to 2 m at two reference points
[205]	PlaceSLAM Uses Bayesian and Particle Filtering	Proximity information	Two office building	Tracking error 2–10 m from pedestrian walking
[204]	WiSLAM, Probabilistic model of Bayesian statics, concerted FootSLAM and PlaceSLAM	Wi-Fi/IMU data	building	Upgrade FootSLAM convergence, accuracy is up to 2 m
[148]	SignalSLAM Modification of GraphSLAM and generate the multi-modal signal maps from available multiple sources	Wi-Fi and Bluetooth RSS/4G LTE, RSRP/magnetic/GPS reference points NFC at specific landmarks and PDR from IMU sensor	Walking naturally around the building	Medium tracking accuracy 11 to 16.5 m

4.8. Machine Learning Localization Approach

Machine learning approaches have been combined with the basic FP deterministic and probabilistic method, for the execution of the classification and clustering purposes of signal measurements in offline and online phases, as presented in Figure 13. The signal measurement method and positioning algorithms are significantly integrated with machine learning [212–215] to predict and estimate the location in indoor wireless localization method, as summarized in Table 6. The current literature considers reducing the location estimation error accumulation, finding the positioning accuracy and efficiency on multipath fading. However, conventional measurement methods are not satisfied with determining these aspects, because indoor localization requires RPs' density from different APs. A machine learning algorithm of supervised learning, regression and unsupervised learning can be used in the classification algorithm, clustering algorithm and matching algorithm, based on useful signals to eliminate the attenuation of the error caused by signal interference from indoor objects and humans. In addition, one of the learning algorithms of neural network type is used in IPS. Extreme learning machine (ELM) is based on the learning algorithm of a single-hidden layer feedforward neural network (SLFN) architecture. Typically, ELM can occupy the fast learning speed as the robust learning technique. ELM can determine the output weighted values from randomly hidden nodes by using the neural networks type too many repetitive times. Regression and classification learning have been conducted with ELM for some existing IPS cause of the good evidence performance in theory. Thus, ELM

is extensively considered for inevitable IPS problems [216–220]. In [217], ELM with dead zone (DZ-ELM) focused on the uncertain data problem creating a dead zone approach to raise the positioning performance inference from the original ELM technique. The several disturbances indoors can be addressed with this approach, that of RSS attenuation and the various changing environments. Although the localization performance of DZ-ELM is better than ELM, the computing time of DZ-ELM is more required. In IPS, the main problems are normally time consumption and manpower usage in offline site survey. In this case, online sequential extreme learning machine (OS-ELM) derives from the obvious benefit of ELM, and it can learn with the fast speed and is more feasible for labour-intensive and computational costs [218,219]. OS-ELM could enable solving the timely manner problem by achieving the performance on the environmental dynamic modes [219]. The experiment was concerned with human behaviour and the status of (opening/closing). In terms of localization accuracy, OS-ELM has a good impact compared to the conventional batch ELM in describing two states. To predict the position under nonlinear RSS measurement, ELM was combined with kernel principle component analysis (KPCA) [216]. Generally, RSS loss and attenuation effect due to multipath propagation are disturbances to estimate the desired accuracy. However, KPCA is utilized to reconstruct RSS new values by extracting RSS features and reducing dimensionality corresponding to a nonlinear signal relationship. These new values were trained through the ELM technique to search the higher localization accuracy.

- Classification algorithm: most of the classification algorithms are based on supervised learning. There are two phases in supervised learning—the training phase and testing phase. In the training phase, received signal strengths need to know their labels to set up the dataset. Then, in the testing phase, the assigned label data need to predict the discrete output values. The classification method under supervised learning, such as NN, KNN, WKNN, SVM, sequential minimal optimization (SMO), Naive Bayes Classifier (NBC), Bayesian network, random forest (RF) classifier, decision tree (DT), boost and bagged were used as a classifier to outperform the indoor positioning methods [213]. Among them, KNN initially emerged as a nearest location estimation in RADAR, which is effective with simplicity. However, it cannot work well for a computational metric due to multiple environmental changes and often has low positioning accuracy. Therefore, the authors in [221] introduced a way to improve the performance of KNN in the field of the GSM network. Popular for indoor positioning, KNN is used for the weighted centroid of relative position for fingerprinting estimation. In addition, the weighted KNN of FP localization and weighted values of RPs certainly depend on their Euclidean distance [222]. The authors in [223] found that fingerprinting localization by using beacon technology (a small radio transmitter) can be combined with a weighted centroid localization method (WCL) and WKNN, in order to reduce the number of RPs over the localization space. NN, KNN and WKNN have been used for the estimation of distance measurements related to the Euclidean distance of a nearest neighbour which has features based on the class of their nearest neighbour in the dataset. WKNN is an extension of KNN, and in that case, the weighted K values are the largest. If all weighted values of WKNN are equal to one, it reduces to the KNN method. In [224], rank-based fingerprinting (RBF) are compared with NN and WKNN in order to investigate the problem of the RSS variant by addressing the drawback without the calibration process. SVM and NBC can also give the desired accuracies for the Wi-Fi fingerprinting system [225]. DT is a tree-like model, in combination with root (nodes), branches (non-terminal nodes) and leaf (terminal nodes). In [226], the authors show the comparison of DT, NN and a neural network based on the WLAN of an indoor environment, in which the location of the user is determined from the DT. Moreover, DT, Adaboost, Bagged, and RF are also used not only as classifiers but also as regression algorithms.
- Clustering algorithm: most clustering problems are solved with unsupervised learning, which can identify hidden patterns from the data analysis and can predict future

values. In indoor localization, K-means, fuzzy C-Mans, neural network, and SVM-C have been used for the implementation of indoor positioning methods. Machine learning of RPs clustering and recognition algorithms can provide the determination of positioning accuracy. The traditional RPs clustering method is needed to pre-define the more accurate positions, since the uncertain number of clusters give rise to poor accuracy [227]. In [228], K-means FP clustering is applied to separate multi-floor levels for a smart building system. In [229], K-means-based approach was used to improve the performance of a distance estimation KNN which determines the close distance values of a mobile user's nearest location. Moreover, the fuzzy C-means clustering method is used to develop KNN performance [230,231].

- Matching algorithm: a matching algorithm aims to find the best match resulting in the correct predicted location between the current FPs' location as measured by the client mobile device in the online phase fingerprinting [232,233]. Although the fingerprinting-based localization algorithm finds the user location, this needs to obtain the exact location of the user inside the indoor environment. Moreover, the FP matching algorithm of WLAN-based positioning could have the enhanced ability for more accurate positioning performance. In [233] is described the superior FPs WLAN system which has a 26% better precision than the conventional fingerprinting localization method. The distance computing of KNN is commonly useful for a matching algorithm as the location determination method. A criticism of KNN is that the software computational time is high in the framework [234,235]. To overcome this problem, the segmentation-based KNN method describing the improvement of the positioning accuracy is 9.24% in the magnetic field indoor location [235]. The magnetometer is one of the IMU sensors that measures the strength of the Earth's magnetic field. In [234] is shown the improvement in indoor positioning accuracy of 91.7% by using a matching KNN algorithm for positioning technology using a geomagnetic field, countering the issues of radio technologies effected from environments, such as multipath noise, human motion and impact obstacles. In [236], the path matching algorithm of indoor positioning for a magnetic field is proposed by solving the time-variant positioning system without influencing radio wave technology. It is certainly true that radio technology benefits wireless sensing networks of a practical indoor location, but there could be environmental influences. The updated indoor positioning system of the Wi-Fi-based RSSI can improve the positioning performance from digital map matching information which makes use of PDR [236–241]. Indoor map matching methods could make use of the information by utilizing smartphones, already making three aspects accessible: mapping path data, user movement activities and position.

Table 6. Performance based on machine learning algorithms and extreme learning machine (ELM).

Approach	Scheme	Moving to Evaluation/Appraisal	Performance/Limitations /Remarks
Classical machine learning	[212]	Utilized Principle Component Analysis (PCA) for extracting data feature from the radio map, time and manpower of computation costs covered with KNN, DT, RF, SVM.	RF 70% in static and KNN 33% in dynamic corresponding to reducing the time, outperforming positioning accuracy.
	[213]	Comparison of the performance of each classification algorithm with the confusion matrix (NN, SMO, DT J48, KNN, AdaBoost, Bagging, Naive Bayes, Bayesian Network), using UJIIndoorLoc database.	Building, floor and region classification, respectively, in which NN showed the best results in accuracy and time depletion.
	[214]	Evaluation of the six location classification algorithms, ANN, KNN, DT, NB, ELM and SVM and then the normalization was performed on the data with the standard score (z-scores) and feature scaling, using the UCI library.	Positioning accuracy relatively with two normalization methods, KNN is superior on these methods 97.98 and 98.75, respectively.
	[215]	Effective for non-linear localization feature extraction leading to mitigate the positioning error from original RSS information with KDDA transform and RVR supports a better regression effect in the reliability system.	Positioning errors are 1.5 and 2 m based on the accuracy of each algorithms.
	[217]	Evaluates higher accuracy based on the uncertainty data with DZ-ELM to increase the original ELM performance, Introduces a dead zone approach for the solutions.	Localization accuracy of 2.19 m DZ-ELM and 2.84 m ELM.
Extreme learning machine	[218]	Uses OS-ELM, ability to reduce computational workload costs in offline calibration survey.	Considers training time, testing time and the average localization performance, localization accuracy under human interference and circumstances of opening/closing doors.
	[216]	Uses KPCA-ELM leading to a fast learning ability and effective accuracy positioning, reduces large data dimension.	Provides a non-linear attenuation effect influence on RSS correlation.

4.9. Filtering Approach

Indoor localization algorithms have been amended with the filtering algorithms to increase the performance of positioning and tracking methods. The filtering algorithms were able to construct the real-time database and compensate for the cumulative positioning error and then it can also remove noise measurements. Bayesian filter [242–244], Kalman

filter (KF) and extended Kalman filter (EKF) [245,246], and particle filter (PF) [247–250] have been implemented by integrating WLAN-based indoor localization determination techniques. The filtering process may aid in obtaining a continuous trajectory and decrease the estimation error.

In the state-space model, the tracking problem can be solved by using Bayesian tracking which is provided by the Bayesian filter. Indeed, a KF, a particle filter and a grid-based Bayesian filter are diverse methods in the overview of the Bayesian filtering process [251]. In [252], a grid-based Bayesian filter is applied to the trusty step length estimation from smartphone data for indoor localization. The main idea of the Bayesian filter is too outperformed as a seamless positioning estimation by considering a complex indoor environment situation. Therefore, in [242] are described efficient conditions and more accurate positioning based on wireless sensor networks in the complexity environment mixing with LoS and NLoS scenarios. In [244], linear and nonlinear models for the location estimation of sensor fusion are considered under a recursive Bayesian Filter by using the location data of dead reckoning and UWB. Moreover, recursive Bayesian filtering, called channel-SLAM, addresses a multipath effect by using a mobile sensor platform.

A particle filter is the iterative estimation method that could take data from human motion, radio map information and RSSI measurements from location APs. In [248], it is proposed that the positioning and tracking algorithm be performed by using an interesting method of signal strength measurement with a particle filter. In addition, the pedestrian map-matching problem can be solved by an accurate positioning and tracking framework with a particle filter by using low-cost smartphone MEMS sensors [239,248,253]. The PF algorithm is a state-equation-based method that has been proven to be suitable for solving the nonlinear filtering problem.

KF and EKF, according to [246], are involved in recursive Bayesian Filter, which has been performed for sequentially investigating positioning in the tracking system. In [254], KF is used for a navigation system upon the motion detection of dead reckoning provided by an MEMS-based INS. KF which solves the linear-quadratic model in real time, and particularly, is used to improve indoor tracking and in navigation applications [247]. It also provides optimal position estimation under accurate measurement modelling and Gaussian measurement noise distribution. Although traditional KF can be achieved for the positioning fusion system under a linear Gaussian model, it cannot solve for nonlinear barriers. It is presented in [255] that there is a hybrid constrained KF approach for the dynamic Gaussian model. Furthermore, EKF has been advocated in advanced nonlinear system processes. EKF is commonly used for the probabilistic mapping problem in SLAM. However, there have some assumptions in EKF-based SLAM that require an updated time for sensor data and for truly known mapping between the observation and landmark [256], leading to important solution methods of the Fast SLAM algorithm. The authors in [247] introduce Bluetooth-based positioning by using indoor map information with the EKF algorithm. EKF, used for the nonlinear models by using the Wi-Fi signal and PDR [257], are also applied to eliminate the noise and are used in linear Gaussian theory.

4.10. Reference-Free Approach

Anchor-free localization procedure does not require an anchor or only requires selecting some anchor nodes during the localization process [258]. In a mobile network over time, the estimation of node position is difficult without prior knowledge of node or pre-surveyed reference node (anchor node). The problem was addressed in [259] by using odometry data and UWB range measurements in a multidimensional scaling (MDS) framework. The MDS paradigm was exploited for both measurement data in this anchor-free indoor tracking system. The proposed system can estimate the node's path jointly with all others. This approach only needs a small number of assumptions and keeps the reference frame through time steps. Therefore, the authors extended this work to make available a real-time tracking system [260]. In this system, the results show that MDS-based approaches are better than the EKF method. The advantage of these approaches

is the ability to evaluate the positions without pre-surveyed reference nodes. In [261], an anchor-free positioning system was presented based on single UWB measurements. Using a factorization-based method and nonlinear least squares (NLS) optimization estimated the position of the nodes. In addition, a semi-automatic method was used to obtain an initial estimation. Another reference-free localization is the footstep-tracker approach, which used accelerometers and gyroscopes in [262].

4.11. Uncooperative Localization Approach

The device localization methods are essential work in wireless security systems and radio management systems. Therefore, a few studies have focused on these localization systems and the difficulty of a transmitter localization of radio frequency energy. One approach introduced a three-dimensional algorithm to obtain the accurate localization of an unknown emitter in an indoor environment [263]. This system was constructed with received signal strength difference (RSSD) information and factor graph (FG), which is good for LoS and NLoS situation. The proposed method considered the stochastic properties and the Gaussian assumption of measurement errors. In this system, the positioning performance has a higher KNN and least squares algorithm. In addition, it shows the mean error below 1.15 m.

On the other hand, there are several works that have been presented using RSS calibration measurements between anchor nodes for indoor localization. However, some works have considered directly measuring the transmitter location from the RSS by dropping this requirement. For instance, the uncooperative emitter localization system was developed in [264,265], which used a listen only uncalibrated receiver. In this approach, the authors developed the bias effects such as additive random variables for an individual receiver in the path loss model. The unknown bias and noise variance parameters were estimated by the variance least squares. Then, the NLS and the Gaussian particle filter (GPF) algorithms were used to handle these bias effects. Another non-cooperative emitter localization focused on enhancing wireless security with only a single receiver [266]. In this system, 3D signal characteristics have extracted for room-based transmitter localization by the development of a vector sensor and compared with traditional methods. The machine learning method utilized for room localization using wavelet transform and the short-time Fourier transform. The results of the room localization performance were higher than TOA, DOA, and RSS. The accuracy achieved above 90% for wideband and narrowband wireless communication signals.

5. Conclusions

This paper reviews the comprehensive description of radio wave signals for indoor positioning, based on common technologies and effective positioning methods. Additionally, the behaviour of non-radio wave signals was mentioned in the introduction section. As mentioned before, the existing positioning algorithms have addressed the inaccurate positioning issue due to the signal variance of multipath propagation, hardware and software complexity, real-time processing and the changing dynamic environment. These algorithms noticeably coped with the depletion of battery usage, the reduction in numerous RPs' accumulation and the correctness of the estimated current position. According to workload reduction, radio map construction can increasingly offer precise positioning behaviour for an unknown environment of a large-scale building. The crowdsourcing method can compute the localization accuracy and medium error in the respective area by implementing the calibration effortlessness and mitigation of RSS variation. Occasionally, the collected crowdsourcing data cannot be exchanged during the recording time with a long period in each existing place which causes the multiplicity of smartphones. Alternatively, SLAM also corresponds to the crowdsourcing methods. SLAM typically uses offline data when a person walks through closed loops, whereas, the high computational workload is required to operate the significant result. Regarding the improved accuracy, the integration of the machine learning and filtering approach is reviewed in this paper. Belonging to the

linear and nonlinear constraints, most classification and clustering algorithms are able to compute the accuracy score and predict the value of the nearest location.

Furthermore, the deep learning neural network (DNN) becomes a modernist solution for huge data amounts of multi-story buildings. It can work well in a reduced training data dimension and extract more effective features from successive samples. For indoor location research, statistical and empirical methods will be very effective guidelines upon the different finding ways. Particularly, localization approaches will also confront diverse protocol, latency and different radio waves. Moreover, the accuracy rate relies on the applications' diversity and the performance of algorithms. Location-aware computing is still affirming in the research trend.

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Nomenclature

AGPS	Assisted-global positioning system
AGNSS	Assisted-global navigation satellite systems
AOA	Angle of arrival
ADOA	Angle difference of arrival
APs	Access points
BLE	Bluetooth low energy
CSI	Channel state information
CSMA/CA	Carrier-sense multiple access/collision avoidance
DAS	Distributed antenna system
DOA	Direction of arrival
DL-ELM	Extreme learning machine with dead zone
ELM	Extreme learning machine
DZ-ELM	Dead zone extreme learning machine
DT	Decision tree
EKF	Extended Kalman filter
FTM	Fine time measurement
FPs	Fingerprints
FG	Factor graph
GPS	Global positioning system
GNSS	Global navigation satellite systems
GSM	Global system for mobile communication
GPF	Gaussian particle filter
GP-LVM	Gaussian process latent variable model

IPS	Indoor positioning system
ILS	Indoor localization services
IoT	Internet of things
INS	Inertial navigation system
IR	Infrared
IMU	Inertial measurement unit
IEEE	Institution of Electrical and Electronic Engineering
JDTDOA	Joint direction and time difference of arrival
KNN	K-nearest neighbour
KF	Kalman filter
KPCA	Kernel principle component analysis
LoS	Line-of-sight
LED	Light-emitting diode
LTE	Long-term evolution
LoRa	Long-range radio
LQI	Link quality indication
MEMS	Micro-electro-mechanical-systems
MPS	Magnetic positioning system
MAC	Medium access control
MMSE	Minimum mean square error
MDS	Multidimensional scaling
NLoS	Non-line-of-sight
NFC	Near field communication
NN	Nearest neighbor
NBC	Naive Bayes classifier
NLS	Nonlinear least squares
OSI	Open system interconnection
OFDM	Orthogonal frequency division multiplexing
OS-ELM	Online Sequential extreme learning machine
PDR	Pedestrian dead reckoning
POA	Phase of arrival
PDOA	Phase difference of arrival
PHY	Physical layer
PF	Particle filter
PRS	Positioning reference signals
PDF	Probability distribution function
PCA	Principal component analysis
RSRP	Reference signal received power
RSRQ	Reference signal received quality
RFID	Radio frequency identification
RSS	Received signal strength
RSSI	Received signal strength indicator
RTOF	Round trip time of flight
RTT	Round trip time
RTOA	Round trip time of arrival
RP	Reference point
RF	Random Forest
RSSD	Received signal strength difference
RBPF	Rao-Blackwellized particle filter
RBF	Rank-based fingerprinting

SVM	Support vector machine
SLAM	Simultaneous localization and mapping
SMO	Sequential minimal optimization
SLFNs	Single-hidden layer feedforward neural networks
TOA	Time of arrival
TDOA	Time difference on arrival
TOF	Time of flight
UWB	Ultra-wide band
VLC	Visible light communication
WLAN	Wireless local area network
WKNN	Weighted K-nearest neighbour
WCL	Weight centroid localization
WSNs	Wireless sensor networks
3GPP	3rd Generation Partnership Project

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