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Review

A Review of Wireless Positioning Techniques and Technologies: From Smart Sensors to 6G

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Abstract: In recent years, tremendous advances have been made in the design and applications of wireless networks and embedded sensors. The combination of sophisticated sensors with wireless communication has introduced new applications, which can simplify humans' daily activities, increase independence, and improve quality of life. Although numerous positioning techniques and wireless technologies have been introduced over the last few decades, there is still a need for improvements, in terms of efficiency, accuracy, and performance for the various applications. Localization importance increased even more recently, due to the coronavirus pandemic, which made people spend more time indoors. Improvements can be achieved by integrating sensor fusion and combining various wireless technologies for taking advantage of their individual strengths. Integrated sensing is also envisaged in the coming technologies, such as 6G. The primary aim of this review article is to discuss and evaluate the different wireless positioning techniques and technologies available for both indoor and outdoor localization. This, in combination with the analysis of the various discussed methods, including active and passive positioning, SLAM, PDR, integrated sensing, and sensor fusion, will pave the way for designing the future wireless positioning systems.

Keywords: localization techniques; positioning algorithms; range-free; range-based; tracking techniques; wireless technologies for positioning

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1. Introduction

The wireless communication infrastructure has been rapidly expanding, in terms of coverage, flexibility, and interoperability for accommodating the increasing technological needs. People have the need to locate and orient themselves within their environment, especially in cases of emergency response, such as in the event of a fire, the need for medical help, or after an earthquake, for informing the rescuers for the locations of the survivors. However, localization is also important in non-emergency cases, such as for navigation during driving, guidance in large museums or shopping malls, and finding the nearby places of interest. Localization demands exist in both the indoor and outdoor environment and, particularly, location-based services for precise location information are estimated to grow to $17 billion by 2025 [1]. For outdoor localization, the global positioning system (GPS) is considered to be the de facto technology [2], whereas, for indoors, it is ineffective and suffers from large localization and proximity errors [3]. Additionally, its accuracy decreases dramatically in urban canyons, close to walls, buildings, trees, and underground environments. This is due to the different wireless signals' characteristics in different environments and to the lack of line-of-sight (LoS) between at least three satellites and the receiver. Moreover, the location-based services (LBS), which are a combination of the indoor positioning systems (IPSs) and geographic information system (GIS), can provide the smart device's current position, which can be used for indoor navigation, but also for the advertisement of products and services based on the user's location.

The introduction of wireless sensor networks (WSNs) in recent years has significantly expanded the range of possible applications for the remote monitoring and controlling of specific phenomena or events. WSNs typically consist of a large number of small-in-size sensor nodes with low power consumption and are envisioned for a variety of applications, including fire detection, crop quality monitoring, field surveying, health-related applications (i.e, listing of patients, doctors and supplies, staff and patient tracking, and elderly care), commercial applications (i.e., inventory control and products' tracking), and military applications (i.e., soldier and mines tracking). The localization and tracking capability is an important aspect of WSNs, since the knowledge of the sensor location is needed to make the collected data meaningful for the various applications. Additionally, the Internet of Things (IoT) digitization and datafication, together with the integration of smart devices, made localization of vital importance.

Generally, localization or positioning determines the position of a node by utilizing techniques and wireless technologies characteristics. To achieve that, some transmitting or receiving nodes with known coordinates are required, referred to as "anchors", "beacons", "reference nodes", "base stations", or "access points". Similarly, the nodes with the unknown coordinates that need to be localized are referred to as "targets", "mobile nodes", or "stations", and they can be either the transmitting or receiving nodes. Commonly, the names are associated with the particular wireless technology used. Throughout the present work, the nodes with known coordinates will be referred to as "transmitting nodes" and the ones with unknown locations as "receiving nodes".

1.1. Contributions

This review provides the following main contributions:

- A comprehensive taxonomy of the related literature in wireless positioning systems over the last 30 years classified according to (i) the localization technique and (ii) the wireless technology employed.
- All the different localization methods and wireless technologies explained from first principles, in order to serve as a self-contained source for the interested audience and facilitate the comparison between the different methods.
- A critical analysis of the different techniques and technologies, identifying existing gaps and challenges and recommending research directions for building the positioning systems of the future.

1.2. Related Studies

There have been a number of other surveys/review papers on wireless positioning systems in the last few decades. A comparative analysis of the state of the art is presented in Table 1, with respect to the different signal measurements and localization techniques covered, the environments (indoors, outdoors) and the wireless technologies considered. From the results, it becomes evident that there is not a single review that adequately covers all the different aspects considered. In particular, the majority of the surveys mainly concentrate on the indoor environment, while completely omitting the outdoors. In general, the range-free localization techniques are less discussed, as compared to the range-based (i.e., lateration and angulation). Furthermore, from the wireless technologies, Wi-Fi is mostly discussed, with the rest to be either completely omitted or discussed briefly.

In more detail, in [4], a distinction is made between localization techniques and technologies aiming to provide a conceptual structure. In [5], the WSN localization algorithms are categorised as centralised, distributed, anchor-based, anchor-less, range-based, and range-free. A comprehensive survey is provided in [6], focusing on the localization and positioning of human users and their devices. The localization of the IoT is also analysed, together with numerous emerging IoT technologies. In [7], a comparative study is provided between the following range-free localization techniques: Centroid, Amorphus, APIT, DV-Hop, and DV-HopMax. The pedestrian indoor positioning systems (IPSs) for mass market applications are reviewed in [8], which are classified into network-based, inertial-based, and hybrid-based systems and are analysed in terms of infrastructure and methodology deployed in the mass market. Many of the studies mainly focus on specific localization techniques, such as fingerprinting [2], pedestrian indoor positioning systems [8], mmWave frequencies [9], Internet of Things (IoT) applications and communication technologies [10], narrowband Internet of Things (NB-IoT) [11], signal processing techniques on Wi-Fi sensing [12], acoustic localization systems [13], wireless acoustic sensor networks (WASNs) [14], and visible light communications (VLC) [15]. On the other hand, some of the existing surveys concentrate on a specific domain, such as WSNs [5,16], range-free localization techniques [7,16], and smartphones [17]. A broad overview of Bluetooth, UWB, ZigBee, and Wi-Fi wireless technologies is provided in [18]. On the other hand, in some reviews, the wireless technologies are not included at all, as in [5,7,14,16,19].

Table 1. Comparative analysis for surveys/review papers on wireless positioning systems from the existing literature.

	Signal Estimations				**Localization Techniques**					**Wireless Technologies**													
Ref.	**Time-based**	**Angle-Based**	**RSS**	**CSI**	**Lateration**	**Angulation**	**Range-free**	**Fingerprinting**	**Environment ***	**GNSS-Indoor**	**Cellular-Based**	**FM**	**LoRa**	**Wi-Fi**	**ZigBee**	**Bluetooth**	**UWB**	**Geomagnetism**	**Acoustic**	**VLC**	**RFID**	**IMU**	**IR**
[2]	✓				✓	✓		✓	I	✓	✓	✓		✓	✓		✓		✓		✓		✓
[20]	✓	✓	✓		✓	✓		✓	I/O	✓		✓		✓	✓	✓	✓				✓		✓
[17]								✓	I/O	✓				✓		✓		✓				✓	
[6]	✓	✓	✓	✓				✓	I				✓	✓	✓	✓	✓		✓	✓	✓		
[8]	✓		✓					✓	I													✓	
[9]	✓	✓							I/O		✓											✓	
[10]									I		✓		✓	✓	✓	✓							
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[4]	✓	✓	✓	✓	✓				I					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[5]	✓	✓			✓		✓		I														
[7]							✓																
[21]	✓		✓			✓		✓	I	✓		✓		✓	✓	✓	✓				✓		
[18]														✓	✓	✓	✓						
[16]							✓		I														
[19]						✓		✓	I	✓													
[22]	✓	✓		✓	✓				I												✓		
[23]	✓								I										✓				
[24]	✓	✓	✓					✓	I/O								✓						
[25]							✓		I/O							✓							
[26]	✓		✓					✓	I											✓		✓	
[27]	✓	✓	✓	✓	✓	✓	✓	✓	I					✓	✓	✓	✓				✓		
[28]									I/O	✓													
[29]	✓	✓	✓		✓				I/O	✓	✓			✓					✓	✓	✓		✓

* Environment: Indoors (I) and Outdoors (O).

1.3. Overview

In this review, a thorough and detailed survey of the all the different localization techniques and wireless technologies is provided, together with their challenges and future directions. The goal is to provide comprehensive and detailed insight into the different aspects of localization for both indoors and outdoors environments. The remainder of this paper is organized as follows. In Section 2, the related literature is classified according to the localization technique, while Section 3 discusses the various wireless technologies and how they relate to localization. Section 4 provides a detailed analysis of the existing literature, identifies existing gaps and challenges, and recommends some research directions for building the future positioning systems. The paper concludes with Section 5.

2. Localization Techniques

In this section, we provide a comprehensive review of the existing localization/positioning algorithms and techniques, classified according to the signal measurements employed (i.e., time-based, angle-based, channel-based), the localization methods (i.e., range-based, range-free, ML/AI), and the tracking methods (i.e., DR, Filters, SLAM). The complete classification is shown in Figure 1.

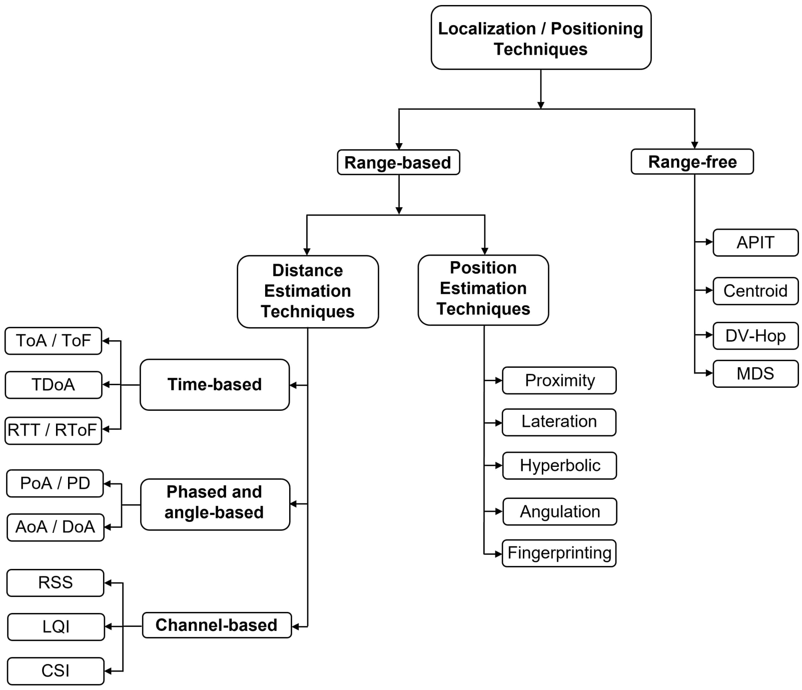


Figure 1. Localization/Positioning Techniques Classification.

2.1. Signal Measurements

The range-based localization techniques rely on the different types of signal measurements for first estimating the distance between the nodes, such as time-based (i.e., time of arrival (ToA), time difference of arrival (TDoA), round trip time (RTT)), angle-based (i.e., phase of arrival (PoA), angle of arrival (AoA)), and channel-based (i.e., received signal strength (RSS), link quality indicator (LQI), channel state information (CSI)). In this section, we describe how the various signal measurements are employed for estimating distance, while a comparison of the different methods is provided in Table 2.

2.1.1. Time-Based Measurements

The time-based measurements are signal propagation delay-based methods for estimating the time lapse between the transmitting and receiving nodes and, as such, can become highly biased from the environment. The time-based measurements include the time of arrival (ToA), the time difference of arrival (TDoA), and the round-trip time (RTT).

Time of Arrival (ToA)

The ToA is a one-way time measurement [30] of the signal propagation time and is used for estimating the distance between the transmitting and receiving node, as shown in Figure 2a. Precise time synchronization between the nodes is required, as well as the timestamp information to be included in the different packets exchanged within the network. The receiving node utilizes the received packets' timestamps for estimating its distance d from the transmitting node, using the following equation [5]:

$$d = (t_1 - t_0) * v, \tag{1}$$

where t_0 and t_1 are the transmitting and receiving time, respectively, and v is the velocity of the signal, i.e., $3 * 10^8$ m/s for radio frequency (RF) or 350 m/s for ultrasound.

Time Difference of Arrival (TDoA)

The TDoA measurements estimates the time lapse between the receiving node and the two signals received from two different transmitting nodes or the two different signals from the same transmitting node, as shown in Figure 2b. For instance, the "Bat" [31] and "Cricket" [32] utilize the RF signal for time synchronization between the transmitting and receiving nodes and the ultrasound signal for ranging. Furthermore, the "BeepBeep" [33] utilizes two devices equipped with microphones and speakers. Specifically, a radio signal is first sent from the transmitting device, followed by an acoustic pulse after a certain period of time. The receiving node records the radio signal timestamp and enables its microphone for detecting the acoustic pulse and recording its timestamp. The TDoA between the two pulses is used by the receiving node for estimating its distance from the transmitting node. In general, compared to ToA, the TDoA only requires time synchronization between the transmitting nodes and can provide higher positioning accuracy. However, this only applies to certain environments with dense transmitting nodes' deployments; therefore, the system's cost can be high [26]. The propagation distance difference $\Delta d_{i,j}$ at the receiving node side can be estimated as follows [26]:

$$\Delta d_{i,j} = d_i - d_j = v(t_i - t_0) - v(t_j - t_0) = v(t_i - t_j) = v\Delta t_{i,j}, \tag{2}$$

where i, j are the different transmitting nodes, or different signals transmitted from the same node, and v the velocity of the signal.

Round Trip Time (RTT)

The RTT requires bidirectional communication between the nodes and the timestamp to be included in the messages exchanged, as shown in Figure 2c. It has been used in some Wi-Fi amendments, such as the IEEE 802.11mc with Wi-Fi fine timing measurement (FTM) [34]. The distance between the two nodes is estimated by:

$$d = \frac{(t_4 - t_1) - (t_3 - t_2)}{2} * v, \tag{3}$$

where t_1 and t_4 are the timestamps of the signal sent and received at the transmitting node, t_2 and t_3 are the timestamps of the signal received and sent at the receiving node, and v is the velocity of the signal.

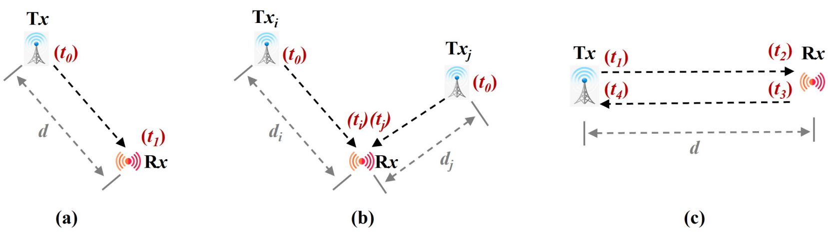


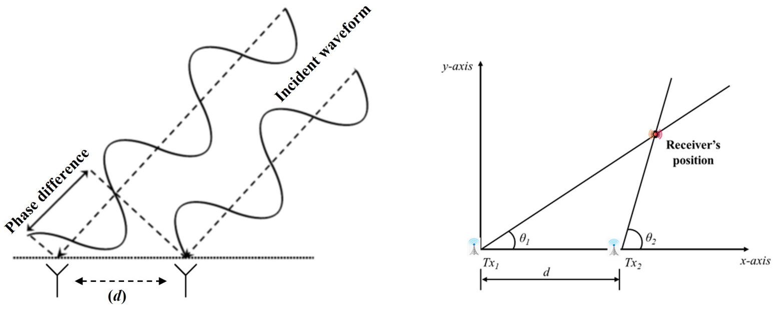
Figure 2. Time-based estimations: (**a**) Time of Arrival (ToA), (**b**) Time Difference of Arrival (TDoA) and (**c**) Round Trip Time (RTT).

2.1.2. Angle-Based Measurements

Angle-based measurements include phase measurements that compare the phase of the signal arriving at the target node (incident signal) with the phase of the signal transmitted and Angle of Arrival (AoA) measurements that utilize the angle between the nodes and the intersection of multiple directions of the wireless signal.

Phase Difference of Arrival (PDoA)

The PDoA utilizes the phase difference of the carrier signal for estimating the distance between the transmitting and receiving nodes. The incident signals arrive with a phase difference at different antennas, as shown in Figure 3a.



(**a**) (**b**)

Figure 3. (**a**) Phase of Arrival (PoA) reproduced with permission from Zafari, A Survey of Indoor Localization Systems and Technologies; published by IEEE, 2019, (**b**) Angle of Arrival (AoA), reproduced with permission from Brena, Evolution of Indoor Positioning Technologies: A survey; published by Hindawi Limited, 2017.

Therefore, the phase difference of the signal received by more than two different antennas at the receiver side is used for estimating the distance between the transmitting and receiving nodes. The distance d is estimated by

$$d = \lambda\left(\frac{\phi_{Rx}}{2\pi} + k\right), \tag{4}$$

where k is a positive integer, λ is the wavelength, and ϕ_{Rx} the phase of the received signal $s(t)$, given by the following sine wave equation

$$s(t) = A\sin(2\pi f t + \phi_{Rx}), \tag{5}$$

where A is the amplitude and f the frequency. Note that the received phase ϕ_{Rx} depends on the distance travelled by the signal, as follows,

$$\phi_{Rx} + 2\pi k = \frac{2\pi f d}{c} \tag{6}$$

where c is the speed of light. By substituting the wavelength as $\lambda = \frac{c}{f}$, then the distance can be directly computed using (4).

PDoA resulting accuracy is generally low and so it is commonly used in combination with other measurements, such as ToA [35].

Angle of Arrival (AoA)

The AoA utilizes the angle between the transmitting and receiving nodes and the intersection of multiple directions of the wireless signal, as shown in Figure 3b. Compared to ToA and TDoA, AoA requires no time synchronization between nodes and its accuracy is proportional to the nodes' density. Its drawback is that additional hardware is required, such as an antenna array. Alternatively, electronically steered antennas can be used for the direction finding. The steerable beam searches for the incoming signal and the received beam determines its direction; therefore, the AoA is estimated at the direction that the received signal power is the highest. Furthermore, directional antennas with a steerable beam can be used for estimating the AoA. Two or more directional antennas with different directions and beam overlapping can be used.

Another way for estimating the AoA is by using subspace-based methods, which decompose the space into signal and noise subspaces and exploit their characteristics, such as the multiple signal identification and classification (MUSIC) algorithm [36]. It deals with the decomposition of the correlation matrix into two orthogonal matrices, the signal and noise subspaces. The direction estimation is carried out from one of these subspaces, with the assumption that the noise in each channel is highly uncorrelated, thus making the correlation matrix orthogonal. Similarly, the estimation of signal parameters via rotational invariant techniques (ESPRIT) [37] use the same model of the signal as MUSIC and significantly reduce the computing power and storage memory. The ESPRIT estimates the direction of arrival (DoA) and time delay of the incoming signals through their eigenvalues. In [37], the performance of both MUSIC and ESPRIT was evaluated using different parameters, and it was concluded that MUSIC is more accurate, while ESPRIT provides better resolution.

2.1.3. Channel-Based Measurements

The channel-based measurements include the link quality indicator (LQI), received signal strength (RSS), and the channel state information (CSI). The LQI is used for evaluating the link quality and the RSS is the actual signal power strength measured at the receiving node. The CSI is an advanced ranging technique used to provide accurate received signal parameters over the entire signal bandwidth [27].

Link Quality Indicator (LQI)

The LQI is a metric of the link quality by measuring the error in the received signal, introduced in the IEEE 802.15.4 (ZigBee), which measures the error in the incoming modulation of the successfully received packets. It is a quality indicator included in all received packets expressed in a range from 0 to 255 that can be used to estimate distance. It can also be used as an assistant indicator of RSS, since it provides a correlation with packet loss (good link quality indicator) [38]. Furthermore, in [39], the LQI was used in an attempt of improving the AoA estimation using the RSSI parameter, with no positive results.

Received Signal Strength (RSS)

RSS indicates the actual power strength measured at the receiving node and is usually provided in decibel milliwatts (dBm) or milliWatts (mW). It is commonly referred as the received signal strength indicator (RSSI) and is usually defined by the chip vendors [6] in a range from 0 to 255. It can be used as an indicator of the distance (link's strength indicator), while each vendor can define its own maximum value. It provides an understanding of location-dependent RSS patterns and underlying location features. The RSS, however, can only provide information about the strength of the signal, while more fine-grained physical layer information can be obtained from the CSI [40].

The RSS measurements are supported by most transceivers, due to their simplicity, and thus, can easily scale to larger areas and multiple users. The distance between the transmitting and receiving nodes is estimated by the signal attenuation of the emitted signal strength by calculating the signal path loss. The path loss is the reduction in power density of an electromagnetic wave as it propagates through space, caused by numerous effects, such as refraction and reflection, as well as the environment and propagation medium. Since the free space propagation model cannot be used for real environments, various distance path loss models are used for estimating the distance. The signal strength is inversely proportional to the distance d and can be estimated by the following formula:

$$P(d)[dBm] = P(d_0)[dBm] - 10n\log\left(\frac{d}{d_0}\right), \tag{7}$$

where n is the path loss attenuation factor, $P(d_0)$ is the signal power at some reference distance d_0, measured in dBm, and d is the distance between the transmitting and receiving nodes. These parameters are usually obtained using statistical evaluation methods based on the collection of field measurements of RSS at predefined positions with known distances to the transmitting nodes. Commonly, the effect of distance on RSS can be measured by the packet success rate provided by the radio. For instance, the RADAR system [41] utilizes the wall attenuation factor (WAF) propagation model (7) for indoors, which includes an attenuation factor for building floors and considers the effects of obstacles, such as walls.

Although RSS is one of the simplest and most widely used metrics, its accuracy is heavily affected by the existence of obstacles and multipath propagation. In [42], real-environment experiments were carried out using smartphones for sensing RSS at various rain rates. The data from the weather stations, including four databases of dry climate and various rain rate conditions, were used for the evaluation. The results confirmed the impact of rain on RSS and that the rain attenuation should be taken into consideration for estimating the distance based on RSS. Although the rain rate was assumed to remain unchanged for a short period of time, the RSS-based distance estimator achieved significant error reduction over the conventional approach.

Channel State Information (CSI)

The CSI is an advanced ranging technique used to provide accurate received signal parameters over the entire signal bandwidth [27]. It represents the channel properties that cause the attenuation of the signal during its transmission between the transmitting and receiving nodes, including multipath. It is only used in the orthogonal frequency division multiplexing (OFDM) systems, in which data is modulated on multiple subcarriers with different frequencies and transmitted simultaneously. The OFDM divides the data stream into multiple sub-streams and transmits them in parallel through multiple sub-channels with orthogonal frequencies. CSI can avoid the multipath effects and noise [40]. In the frequency domain, the CSI is referred as the channel impulse response (CIR), which is a fine-grained physical layer information used to describe the amplitude and phase of each subcarrier. This frequency diversity provides a unique fingerprint, which can be used for constructing a radio map. However, special hardware is required for capturing the state information, such as multiple antennas and advanced network interface cards (NICs), which increase the system's cost and complexity.

The CSI information can be extracted in the frequency domain in the form of a channel frequency response (CFR), which describes the multipath propagation of the signal from the amplitude and phase frequency characteristics. The CSI of a single subcarrier can be expressed as follows:

$$H_i = |H_i|e^{j\sin(\angle H_i)}, \tag{8}$$

where $|H_i|$ is the amplitude response and $\angle H_i$ is the phase response of the i-th subcarrier. In [40], both RSS and CSI measurements were collected at fixed locations and compared. The CSI measurements benefit from multipath effects and, therefore, provide richer and finer information. The signal attenuation ranging model established utilized the attenuation factor propagation model for converting the RSS and CSI measurements into distance values, as follows [40]:

$$d = \alpha * 10^{\frac{A-RSS}{10n}} + (1-\alpha)\frac{1}{4\pi}\left[\left(\frac{c}{\frac{f_0}{K}\sum\frac{f_k}{f_c} * ||A||_k}\right)^2 \sigma\right]^{\frac{1}{n}}, \tag{9}$$

where $\alpha \in [0,1]$, A is the signal strength at 1m from the source, n is the path loss attenuation factor, σ is the environmental factor, c the radio velocity, f_0 is the central frequency of CSI, K is the number of subcarriers, f_c is the calculated center frequency, and $||A||_k$ is the amplitude of the k-th carrier of the filtered CSI. In [40], it was shown that the combination of RSS and CSI can provide more accurate distance information, as compared to only using an existing RSS attenuation model. Additionally, the CSI was found to be more stable in the indoor environment, while employing the ranging algorithm can further improve the ranging stability.

Table 2. Distance Estimation Techniques Comparison.

Distance Estimation Techniques	Features	Limitations
Time of Arrival (ToA)	- More accurate results compared to the RSSI measurements	Precise time synchronization between nodes is required - Highly biased from the environment - Additional hardware may be required
Time Difference of Arrival (TDoA)	- Contrary to ToA, TDoA only requires precise time synchronization between the transmitting nodes - It can also be utilized with nodes equipped with speakers and microphones - Provides higher accuracy than ToA - It can be used with different communication technologies, i.e., ultrasound and RF	- Time synchronization between transmitting nodes is required - Performance is degraded in the NLoS signal propagation - Microphones and speakers require LoS and free of echoes conditions for higher accuracy
Round Trip Time (RTT)	- It eliminates the need of utilizing different clocks and time synchronization	- It requires bidirectional communication capabilities - Its accuracy is biased from the different changes in the environment - Latencies may occur for fast moving devices
Phase of Arrival (PoA)	- It can be combined with other measurements for higher accuracy	- The phase cannot be distinguished, so it can only determine in which fraction of the wavelength a signal is received - It requires LoS
Angle of Arrival (AoA)	- At least two transmitting nodes are required - No time synchronization between the nodes is required	- It requires LoS signal propagation - Signals can easily change direction, so accuracy degradation occurs - Its accuracy is proportional to the nodes' density - Additional hardware is required (e.g., antenna arrays) - Expensive computational cost
Received Signal Strength (RSS)	- One of the simplest and most widely used metrics - Supported by most transceivers - Easily scaled to larger areas and multiple users - Minimum infrastructure required - Cost-effective computation	- Its accuracy is affected by the existence of obstacles and multipath propagation - Affected by NLoS - Affected by weather conditions, such as rain [42] - Less accurate than time-based estimations
Link Quality Indicator (LQI)	- Contrary to RSS, LQI is included in all received packets	- Only available for ZigBee technology
Channel State Information (CSI)	- It can be used as a unique fingerprint - More accurate estimates, compared to the RSS estimations	- It can only be used with technologies supporting OFDM - Special hardware is required (increased cost and complexity) - It is affected by the dynamic changes of the transmitting nodes' power

2.2. Range-Based Localization Techniques

Range-based localization techniques first utilize the signal measurements (time, angle, or channel-based) for estimating the distance/range from various reference nodes, as described in Section 2.1. Next, the various distance measurements are combined using appropriate algorithms for estimating the nodes' unknown positions. The methods described in this section include lateration, hyperbolic, angulation, and multidimensional scaling (MDS).

2.2.1. Lateration

The unknown position of the receiver node is estimated by using different range measurements, such as RSS, ToA, and TDoA, from multiple transmitting nodes with known locations. More specifically, a theoretical circle is first formed according to the estimated range from each known transmitting node, indicating the possible positions of the receiver. For a single transmitting node, as shown in Figure 4a, the receiving node can be located anywhere on the circle circumference. By adding another transmitting node, as shown in Figure 4b, then the receiving node can be located on any of the two intersection points formed. Finally, by adding a third transmitting node, as shown in Figure 4c, it eliminates the ambiguity to a unique point, which is the intersection of the three circles. The minimum requirement is three non-collinear transmitting nodes for trilateration (2D space) and four for multilateration (3D space). In error-free environments, these theoretical circles or spheres intersect at a single point, indicating the spatial position of the receiving node. However, in real-world applications, the circles do not necessarily meet at a single point, due to noise, and so a possible region is formed, instead, from which a single point is selected as the best guess using the least squares methods.

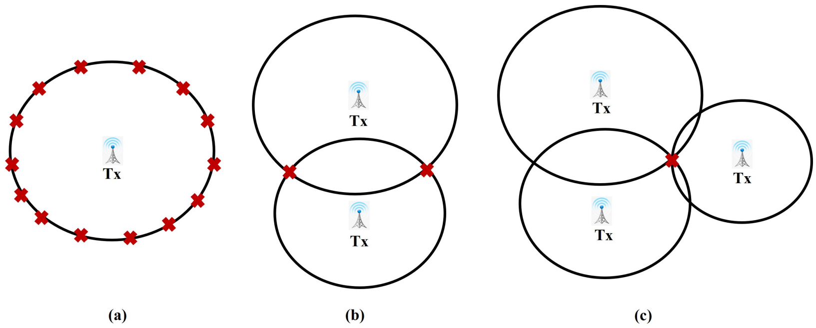


Figure 4. Trilateration localization technique. (**a**) The receiving node can be located anywhere on the circle circumference; (**b**) the receiving node can only be located on any of the two intersection points; (**c**) the receiving node can only be located on the intersection of the three circles.

The circumference of the circle or sphere for the 2D or 3D space, respectively, are commonly estimated using the Euclidean distance. For the trilateration, three quadratic equations are formed:

$$(x - x_A)^2 + (y - y_A)^2 + (z - z_A)^2 = d_1^2 \tag{10}$$

$$(x - x_B)^2 + (y - y_B)^2 + (z - z_B)^2 = d_2^2 \tag{11}$$

$$(x - x_C)^2 + (y - y_C)^2 + (z - z_C)^2 = d_3^2 \tag{12}$$

where (x_A, y_A, z_A), (x_B, y_B, z_B), and (x_C, y_C, z_C) are the known coordinates of the transmitting nodes, (d_1, d_2, d_3) are the estimated distances between the receiving and transmitting nodes, and (x, y, z) are the unknown receiver's coordinates.

2.2.2. Hyperbolic

The hyperbolic localization technique utilizes the TDoA measurements. Each TDoA provides a hyperbolic curve in the localization space, as shown in Figure 5, on which the position of the unknown receiving node lies, and their intersection provides a unique position.

Specifically, the known transmitting nodes represent the foci of the hyperbola, while the different hyperbolic curves formed represent the different transmission times. The unknown receiving node is assumed to lie on the hyperbola, whose foci includes the known anchor nodes 1 and 2, with the focal length corresponding to their distance difference $\Delta d_{1,2}$. By adding another transmitting node, an additional hyperbola is formed, whose foci includes the known anchor nodes 1 and 3, and the focal length is their distance difference $\Delta d_{1,3}$. The uncertainty is reduced, and the unknown receiving node position is estimated at the intersection of all the hyperbolae. For the 3D space, the difference in distance Δd is estimated by using the Euclidean distance, as follows:

$$\Delta d_{2,1} = \sqrt{(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2} - \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} \quad (13)$$

$$\Delta d_{3,1} = \sqrt{(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2} - \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} \quad (14)$$

which can be re-written in the following general form:

$$\Delta d_{i,1} = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2} - \sqrt{(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2} \quad (15)$$

where (x_i, y_i, z_i) are the known i-th transmitting node's coordinates.

Solving these nonlinear hyperbolic equations can be challenging, and numerous methods involving a Taylor series expansion and transformation into a linear set of equations are commonly used. Alternatively, the Chan's, Foy's, Fang's, and Friedlander's methods can be used, which were evaluated in [43]. It was concluded that the Chan's method is the best available option for solving the hyperbolic equations, at the expense of a priori knowledge of the approximate locations and distance between the various transmitting nodes and the first transmitting node.

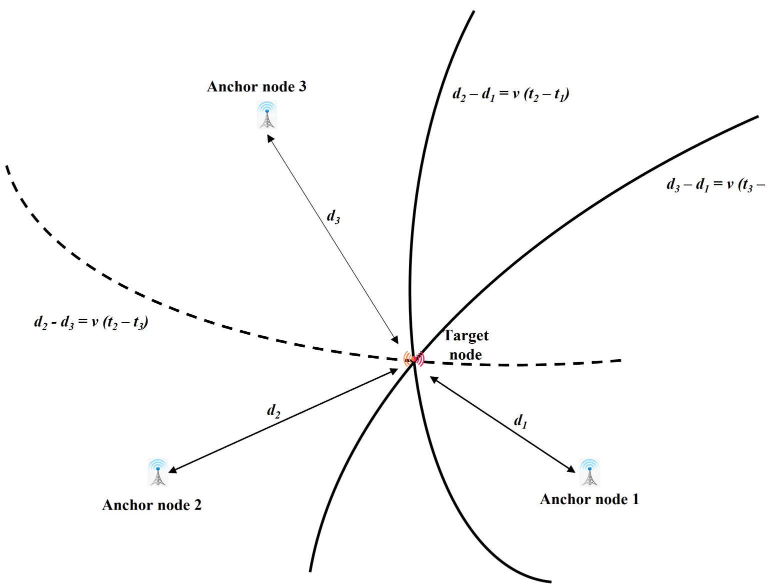


Figure 5. Hyperbolic localization technique, reproduced with permission from Zafari, A Survey of Indoor Localization Systems and Technologies; published by IEEE, 2019.

2.2.3. Angulation

The angulation process aims to determine the unknown location of the receiving node by estimating the angles from the corresponding known transmitting nodes. The triangulation localization technique mainly utilizes the AoA estimations from at least two known transmitting nodes and provides a moderate precision. At least two transmitting nodes are required, and the LoS conditions and the position of the receiving node (x, y) can be directly estimated, as follows:

$$x = \frac{d\tan(\theta_2)}{\tan(\theta_2) - \tan(\theta_1)} \tag{16}$$

$$y = \frac{d\tan(\theta_1)\tan(\theta_2)}{\tan(\theta_2) - \tan(\theta_1)}, \tag{17}$$

where θ_1 and θ_2 are the angles formed by the two transmitting nodes, and the distance d between the two transmitting nodes given by:

$$d = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}, \tag{18}$$

where (x_1, y_1) and (x_2, y_2) are the transmitting nodes' coordinates.

Its accuracy depends on the precision of the AoA estimation; therefore, its localization performance is proportional to the known transmitting nodes' density [27,44]. For the angulation technique, directional antennas can be utilized for identifying the intersection of the two line of bearings, at the expense of increased system's cost. Moreover, angulation is affected by multipath under NLoS propagation conditions, which can lead to localization errors [22]. Similar to trilateration, triangulation is based on an ideal model of the wireless propagation. Therefore, these techniques may be unreliable in the presence of effects that are not included in the models, for instance, important information may be lost, since it is not practically feasible to measure the calibrated antenna pattern for every single node [24].

2.2.4. Multidimensional Scaling (MDS)

The multidimensional scaling (MDS) localization technique is a dimensional reduction technique that converts the multidimensional data into a lower dimensional space, while keeping the essential information [29]. In more detail, the distance between all pairs of nodes is first obtained by utilizing any ranging technique for creating the MDS distance matrix. Then, the shortest path algorithm is applied, such as Floyd's or Dijksta's algorithms. Next, the matrix of the squared distances of proximity is computed and double centering is applied. Singular value decomposition (SVD) follows, which is a matrix decomposition method for reducing a matrix, and the relative matrix coordinates are obtained and transformed to an absolute map by using the known transmitting nodes. Finally, the matrix is rotated, translated, and shifted for achieving the same orientation as the original one [45].

The aim is to find a low dimensional representation of a group of objects, such that the various distances between the objects fit, and a given set of measured dissimilarities indicating the dissimilar objects. For this, a central processing unit for collecting all available dissimilarities and performing the function minimization is required. In [46], the MDS technique was used for the CSI fingerprinting dimension reduction, in combination with the triangular centroid algorithm, aiming for real-time positioning. Alternatively, the MDS can be combined with the refinement and trilateration (MDS-RT) by adjustment [45], with the aim of improving the accuracy of the localization. In this context, the trilateration is used as an optimization tool for eliminating the MDS poor accuracy. In addition, distributed weighted multidimensional scaling [47], as well as combining MDS with the multilateral algorithm [48], have accurate range measurements. It was also employed in [49] for improving the distance estimation for three-dimensional (3D) nodes localization.

2.3. Range-Free Localization Techniques

Range-based localization techniques first utilize the signal measurements (time, angle, or channel-based) for estimating the distance from various reference nodes, followed by the various localization algorithms described in Section 2.2 for estimating the nodes' position. On the other hand, the range-free methods utilize the topological information of the sensor nodes (i.e., the number of hops) [7] for directly estimating the position. Although the range-based methods provide higher accuracy, they require additional hardware and, thus, higher cost and deployment complexity. On the other hand, the range-free methods require no additional hardware, which makes them more cost effective at the expense of lower accuracy levels [50]. In this section, we provide an overview of several popular range-free localization algorithms, including proximity detection, centroid, distance vector (DV)-hop, APIT, and SNAP.

2.3.1. Proximity Detection

It is one of the simplest position estimation algorithms and provides relative location information based on the range of known transmitting nodes. The unknown receiving node's position is estimated based on the strongest signal strength, and the relative location is derived from the antenna grid when it is within the radio signal range. Its accuracy is proportional to the transmitting nodes' density. Specifically, each transmitting node creates a theoretical circle, which indicates its coverage region, as shown in Figure 6. The circle diameter is determined by the signal power. The receiving nodes scan the radio signal channel and are classified as being within the region (i.e., Rx_1) or outside the region (i.e., Rx_2). It can only provide room-level accuracy for indoors and cell-level for outdoors. For instance, the GSM-based localization is within a range of 50–200 m coverage, which corresponds to the size of the GSM cell [20]. Moreover, proximity is utilized by the RFID-based anti-theft systems, as well as the BLE beacons, such as the iBeacon and Eddystone introduced by Apple [3] and Google [5], respectively, with various applications including hotels and airports.

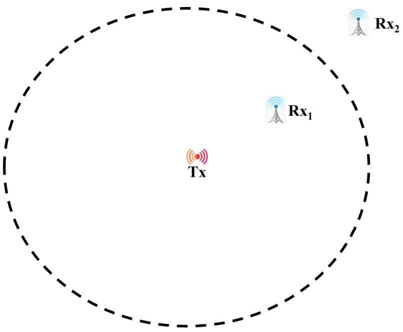


Figure 6. Proximity localization technique, reproduced with permission from Zahid, Recent Advances in Wireless Indoor Localization Techniques and System; published by Hindawi Limited, 2013.

2.3.2. Centroid

The centroid localization technique estimates the receiving node's position as the centroid of all transmitting nodes' positions with minimum computations. Similar to the proximity technique, the receiver node first identifies whether it is located within the communication range of the known transmitting nodes. Next, the receiving node determines its location by using the mean of all coordinates of all the known transmitting nodes located within the threshold region by using the following equations [50]:

$$x_u = \frac{\sum_{i=1}^{m} x_i}{m}, \qquad y_u = \frac{\sum_{i=1}^{m} y_i}{m}, \tag{19}$$

where (x_u, y_u) are the coordinates of the receiver node, (x_i, y_i) are the anchor nodes' coordinates, and m is the total number of known transmitting nodes located within the coverage region of the receiver node.

Although the centroid localization technique is easy to implement, its accuracy depends heavily on the environmental propagation conditions and the density of anchor deployment.

2.3.3. Distance Vector (DV)-Hop

The distance vector (DV)-hop localization technique is a distributed range-free algorithm based on the distance vector routing protocol. Similar to the other range-free localization techniques, all the network nodes are assumed to broadcast their localization information and estimate their distance to the other nodes, so that all nodes acquire the last hop count required to reach each other [28]. In more detail, the DV-hop algorithm consists of three steps. Firstly, the network minimum hop count is estimated. Secondly, the average hop distance and the distance between the known transmitting and unknown receiving nodes are estimated. Finally, the unknown receiving nodes' coordinates are estimated. The broadcast information includes the identifier id, coordinates (x_i, y_i), and hop count for each transmitting node i. Initially, the hop_i parameter is set to zero, and for each broadcast packet, it is compared with the previous recorded value and updated accordingly. Therefore, each receiving node R_i receives the location coordinates, together with the hop count values, from all other transmitting nodes, so it can compute the average distance per hop by using the following formula [28]:

$$HopDistance_{R_i} = \frac{\sum_{i \neq j} \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}}{\sum_{i \neq j} hop_{ij}}, \tag{20}$$

where (x_i, y_i) are the coordinates of node R_i, and hop_{ij} is the number of hops from R_i to R_j. Finally, the average distance per hop $HopDistance_{R_i}$ is broadcast from the unknown receiving node R_i, and each sensor node N computes its estimated distance from the receiving node R_i using the following equation [28]:

$$distance_{N,R_i} = HopDistance_{R_i} * hop_i, \tag{21}$$

where hop_i is the number of hops between N and R_i. When at least three receiving nodes have been identified, then node N can use triangulation and estimate its position. The main drawback of the DV-hop localization technique are the assumptions made, i.e., that the paths are in a straight line or that the nodes are distributed evenly, which can result in errors when estimating the actual distances. Moreover, a combination of DV-hop with range-based measurements can be utilized for improving the localization accuracy, for example, in combination with RSS measurements [51]. Similarly, other range-free position estimation techniques, such as the centroid [52], can also be used.

2.3.4. Approximate Point in Triangulation (APIT)

The APIT localization technique is a geometric algorithm that utilizes triangular areas and is based on the assumption that all the known transmitting nodes in the WSN broadcast their information within a certain region. It provides a high level of precision by an approximation method, at the expense of high density and a large communication radius for the known transmitting nodes [53]. It is an area-based approach that separates the area into triangular regions formed by the transmitting nodes by assuming that the nodes are stationary. The unknown receiving nodes are determined as being inside, as shown in Figure 7a, or outside, as shown in Figure 7b, of the triangular regions formed. The "point in triangulation" procedure starts with three known transmitting nodes forming triangles, and it continues for all the remaining nodes.

The test criteria includes the unknown receiving node to be defined as being *inside* the △ABC and after changing its position in any direction becomes either nearer or farther away from the three vertices of the triangle. It is defined as being *outside* the △ABC and after changing its position in any direction, to be either nearer or farther away from the three vertices of the triangle. This test criterion causes some errors, such as the "InToOut" and "OutToIn" errors, as shown in Figures 7c,d, respectively. The first error is caused when the unknown node is located inside the triangle, but the test criteria locates it as being outside the triangle. This is commonly caused when the node is located near the edge of the triangle and farther from all points of the △ABC. This error can be eliminated by using the Barycentric coordinate technique [53], which uses three scalars, and the unknown receiving node can be located either inside the triangle or on any one of the edges or vertices of the △ABC. Similarly, the latter error is caused by the irregular placement of neighbours, which mistakenly conclude that the unknown node is located inside the △ABC. Alternatively, the APIT limitations can be addressed by using collaborative positioning for decreasing the node positioning error and increasing the localization coverage area, as in collaborative coefficient-triangle APIT localization (CCAL) [54]. It improves the outside criterion by utilizing a threshold for determining the number of neighbouring transmitting nodes outside the triangle.

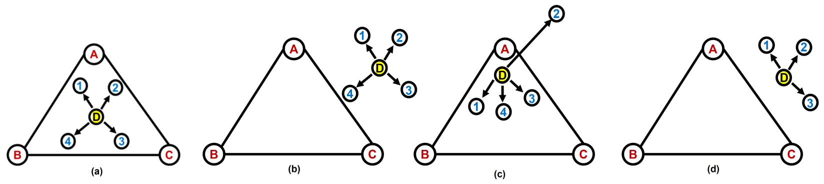


Figure 7. Approximate Point in Triangulation (APIT) localization technique, reproduced with permission from Chen, An Indoor Collaborative Coefficient-Triangle APIT Localization Algorithm; published by MDPI, 2017. (**a**) The receiving nodes are determined as being inside the triangle; (**b**) the receiving nodes are determined as being outside the triangle; (**c**) "InToOut" error; (**d**) "OutToIn" error.

2.3.5. Subtract on Negative Add on Positive (SNAP)

The SNAP [55] algorithm assumes the use of binary sensors and maximum likelihood estimation for localization. The likelihood matrix is constructed by using the $(+1)$ and (-1) contributions from the sensor nodes, depending on their alarm state. Each alarmed sensor adds a positive one contribution to the elements of the likelihood matrix, which correspond to the cells inside its region of coverage (ROC), whereas the non-alarmed sensors add a negative one. It is a fault-tolerant algorithm capable of identifying the event location by using only binary sensor data, as well as promoting the sensor collaborative efforts. Each sensor has a coverage area (ROC), and the source creates a corresponding area around its location, the region of influence (ROI), which is defined as the area that the sensor nodes will be alarmed with high probability (at least 0.5). For example, Figure 8 shows an example of using the SNAP algorithm with eight sensor nodes, three of which are alarmed (solid colour), and the event is correctly localized in the cell with the maximum value $(+3)$.

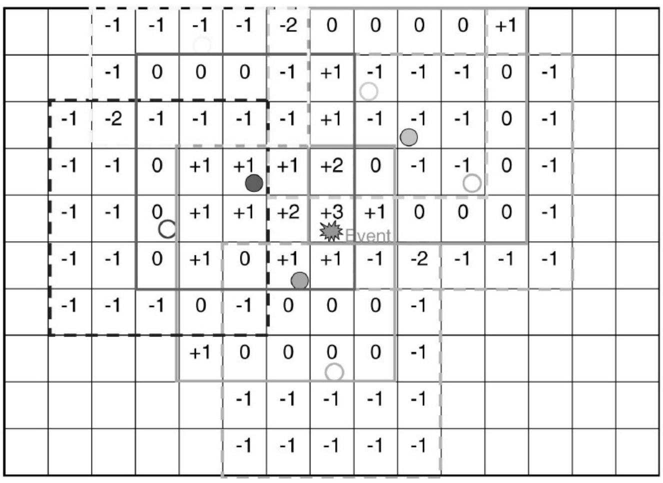


Figure 8. Subtract on Negative Add on Positive (SNAP) reproduced with permission from Michaelides, SNAP: Fault Tolerant Event Location Estimation in Sensor Networks Using Binary Data; published by IEEE, 2009.

The SNAP limitations include the assumptions that (i) the sensor nodes are static and uniformly spread over a rectangular area, (ii) the source of the event continuously emits a uniform signal in all directions, and (iii) no environmental changes occur. Nevertheless, compared to the centroid or classical maximum likelihood estimation, the SNAP is more fault tolerant and demonstrates robust behaviour to sensor position errors. Depending on the sensor node density, it can achieve similar accuracy with maximum likelihood estimation at a very low computational cost.

2.4. Machine Learning (ML) Localization Algorithms

The machine learning (ML) localization algorithms have emerged as a powerful framework for solving many challenging practical problems and addressing the limitations of the conventional techniques, especially for the indoor localization systems [27]. ML, in general, describes the capacity of systems to learn from problem-specific training data to automate the process of analytical model building and solve the associated tasks. It utilizes real-world data for training and capturing the complex relations between the input data (features) and output values (labels) [24]. For localization, the output variables can consist of discrete values (categories), such as "within zone" or "outside zone", or a range of continuous values, such as the RSS of the signal over time. Both classification and regression problems can be applied, such as finding a point on a finite grid that best fits the observed input data and estimating the coordinates of the device. Numerous algorithms exist for supervised, unsupervised, and reinforcement learning, such as the k-nearest neighbour (k-NN), artificial neural networks, Bayesian inference, support vector machines (SVMs), or their combination [22,24].

More recently, deep learning (DL) approaches including recurrent neural networks (RNNs) have also been investigated for building positioning systems [56]. In [57], a mobile positioning system was built with a mobile station, a mobile positioning server, a database server, and a model server. The mobile positioning server handled the collection and normalization, mobile positioning method, de-normalization, and estimation. The database server included the network signal and GPS coordinates, while the model sever included the recurrent neural networks (RNNs). The model server could save the trained RNN models from the positioning layer (base stations and Wi-Fi APs normalized RSSIs), a recurrent hidden layer, and the output layer (estimated normalized longitude and latitude). For the optimization of recurrent neural networks, the learning rate and the gradient descent method is applied to update each weight and bias. On the other hand, deep learning requires large scale annotation of the models training, which can be challenging [58]. Nevertheless, the deep learning techniques may be more adopted for indoor positioning in the near future [59].

Fingerprinting

Fingerprinting is one of the most commonly used ML localization techniques in the literature [60]. It mainly relies on the analysis of specific measurements or features of the signal received by the unknown receiving node. It consists of the offline data collection phase and the online matching phase, as shown in Figure 9.

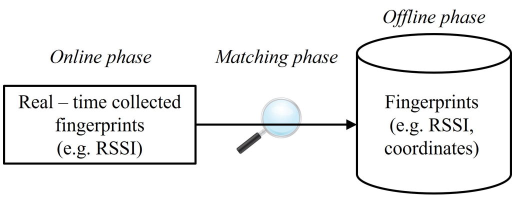


Figure 9. Fingerprinting localization technique, reproduced with permission from Khudhair, *Wireless Indoor Localization Systems and Techniques: Survey and Comparative Study*, published by Indonesian Journal of Electrical Engineering and Computer Science, 2016.

During the offline phase, a site survey is carried out consisting of the unique location fingerprints, i.e., signal characteristics, coordinates of sampling points, and signal strength [22]. It can be classified as either deterministic or probabilistic [24]. The deterministic approach involves the storing of different fingerprints, whereas the probabilistic computes some statistic of the measurements first, such as taking a simple average of the RSS measurements. The deterministic requires less calibration effort, while the probabilistic requires the computation of the statistics for each calibration point [8]. Furthermore, during the online phase, real-time measurements are collected and compared with the already stored ones from the offline phase. This comparison occurs during the matching phase and is commonly based on a matching score [30], thus finding the best match between the stored and real-time fingerprints, which involves simple matching techniques, i.e., distance estimations and cross correlation metrics [24,27]. The *k*-NN is one of the most commonly used ML algorithms for performing the matching.

Fingerprinting approaches for localization, however, require large sets of training data, which are sometimes difficult to collect. In particular, the training and computational complexity requirements remain significant challenges, especially when they occur on low computational power devices. The usage of sensor fusion on the server side can assist, but at the expense of increased latency, which is a problem for real-time positioning systems [24]. Moreover, in the 2019 IPIN competition, some competitors argued that the fingerprinting techniques are not a viable solution for future indoor localization systems [59]. The system's scalability is another ML challenge, as well as the time-consuming procedures for the collection and comparison process. The comparing process time can be reduced by dividing the database into numerous clusters and comparing data from the target node only with the data in the corresponding cluster [27]. Similarly, the Support Vector Machines (SVMs) algorithms can be used for increasing the flexibility of the ML. In particular, they can adopt kernel mechanisms for finding the difference between two points of two separated classes, as well as modeling the linear and non-linear relations with better generalization performance. In addition, they can utilize the different channel characteristics and identify the LoS and NLoS classes [9]. Still, SVMs are characterised as time-consuming algorithms with high memory requirements, especially when the number of support vectors becomes large [27].

For instance, the "RADAR" [41] pioneered the fingerprinting by utilizing the Wi-Fi technology, and since then, it has been a popular localization technique, with RSS measurements collected from various Wi-Fi access points (APs). The RSS can be used in combination with CSI, since the main path of the received signal can be easily distinguished from the reflected signals, and CSI provides more information, compared to RSS fingerprinting [40]. Fingerprinting complexity and costs are significantly low, since no additional hardware deployment and time synchronization between the nodes are required. Although it is a simple, easily adaptable and inexpensive technique, its updating and maintenance are challenging, due to its sensitivity to the environment changes [24,27]. For cost reduction, volunteers and self-guided devices are commonly used for the signal's features collection and radio map creation.

Although it is mostly used for indoors, in [61], fingerprinting was used outdoors for comparing different wireless technologies, such as SigFox and LoRaWAN. Analytically, three SigFox datasets were collected in rural and urban areas, as well as a LoRaWAN dataset in an urban area. All datasets contained the GPS coordinates, the RSS, and other additional measurements for each particular location. Each fingerprint distance was estimated by using the Euclidean distance, and the centroid of the *k* nearest fingerprints was used as the location estimation. It was concluded that the fingerprinting localization technique provided a high level of accuracy and reliability for both tested wireless technologies.

2.5. Tracking Techniques

The tracking techniques can be characterised as continuous localization techniques, thus tracking an object's position for a specific period of time. They usually rely on specific hardware, which is exposed to the environment; therefore, the system's surroundings are of vital importance for tracing a position accurately. The hardware for outdoors applications includes satellites and cell towers, whereas for indoors, sensors and cameras are commonly used. The use of a camera can enable the tracking an object in a 3D space; the Accuware [62] and the commercial car parking guidance system [63] are good examples of camera-based tracking systems.

Moreover, a comprehensive overview of the tracking systems participating in the Indoor Positioning and Indoor Navigation (IPIN) competition in 2019 and 2020 is provided in [58,59], respectively. The competitions mainly consisted of smartphone-based systems with sensor fusion, which could accurately identify and track their position. A variety of different systems and techniques were utilised for the competitions, including PDR systems mounted on the foot of the pedestrian, positioning systems based on augmented reality (AR) and mixed reality, localization algorithms using particle filters, and multi-sensor fusion systems combining wireless signals, such as Wi-Fi, with information from various sensors, such as magnetometers, accelerometers, gyroscopes, and light sensors (luxmeters). Some systems were designed for discriminating the indoor and outdoor environment, i.e., by utilizing the luxmeter sensor. In particular, the competition area included an outdoor scenario, with a satellite view and an indoor scenario without satellite view, and the competitors had no prior knowledge of the test route; therefore, they could only rely on their smartphone to calculate the vehicle position. In such scenarios, a variety of tracking techniques and wireless sensors can be utilised, such as the fusion of GNSS and inertial navigation system (INS), together with filters, such as the extended Kalman filter (EKF), or neural networks.

In this section, three of the most popular tracking algorithms are discussed: the dead reckoning, filters, and SLAM.

2.5.1. Dead Reckoning (DR)

The DR tracking algorithm estimates the change from the last known position. The receiving node's current position is estimated based on the previous determined positions, orientation, and speed. The initial position, orientation, and velocity must be known a priori. For instance, the pedestrian dead reckoning (PDR) is used for approximating a pedestrian's relative position against a defined location and can be classified as the strapdown inertial navigation system (INS) or the Step and heading system (SHS), shown in Figures 10 and 11, respectively.

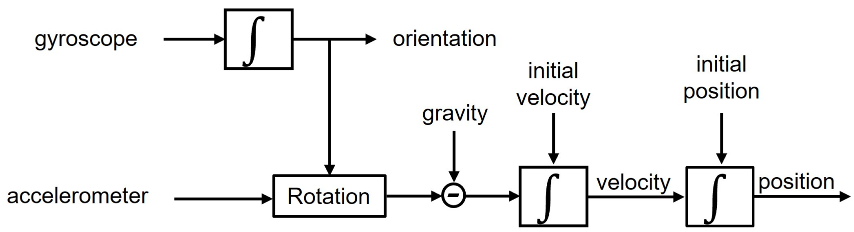


Figure 10. Strapdown Inertial Navigation System (INS), reproduced with permission from Correa, *A Review of Pedestrian Indoor Positioning Systems for Mass Market Applications*, published by MDPI, 2017.

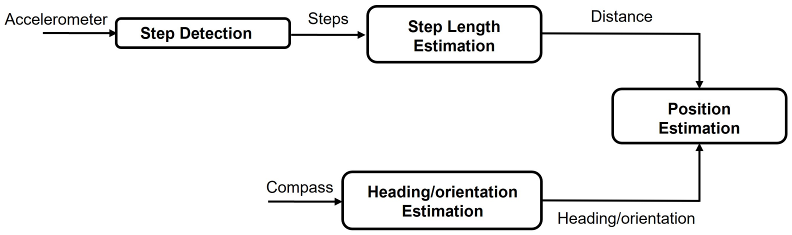


Figure 11. Step and Heading System (SHS), reproduced with permission from Ashraf, *Smartphone Sensor Based Indoor Positioning: Current Status, Opportunities, and Future Challenges*, published by MDPI, 2020.

Both INS and SHS estimate the pedestrian's position and orientation by using the accelerator's and gyroscope's measurements, as well as the user's step length and heading [8,17]. Analytically, the INS utilizes the gyroscope and stride through the double integration of the combination of the accelerometer and gyroscope data. The rotation transformation is then used for transforming the non-inertial reference frame (the one attached to the sensor) to the inertial reference frame. The obtained result is integrated twice for obtaining the position estimation. The integration operand commonly results in acceleration errors, which can be eliminated by subtracting the gravitational field g before the integration, as follows:

$$v(t) = v(0) + \int_0^t (a(t) - g)dt. \tag{22}$$

On the other hand, the SHS detects the pedestrian's steps by using the acceleration measurements. The body movements cause acceleration signal rises, called peaks, followed by a signal fall. For determining the number of peaks, numerous threshold-based methods can be used. The steps counting, together with the compass or gyroscope measurements, are used for estimating the pedestrian's heading and position by using the following equations [8]:

$$m_x(k) = m_x(k-1) + l_{step}(k)\cos(\theta(k)) \tag{23}$$

$$m_y(k) = m_y(k-1) + l_{step}(k)\cos(\theta(k)), \tag{24}$$

where m_x and m_y are the x and y components of the position, respectively, k is the time index, l_{step} the step length, and θ is the heading.

Similar to INS, the SHS heading is estimated by using the integration of the gyroscope signal, which causes accuracy limitations, due to the gyroscope errors [64]. Therefore, the final position can drift, so an alternative solution is the utilization of the magnetometer measurements, at the expense of degraded accuracy, due to the spanning over a long period of time and bias from the external ferromagnetic interference. The optimum solution may be the fusion of different sensor measurements, i.e., the gyroscope and magnetometer, the accelerometer and gyroscope, or the accelerometer and magnetometer. In [64], the combination of the accelerometer, gyroscope, and magnetometer measurements is effectively used for reducing the accumulated errors. Moreover, in [17], the deployment of body-mounted sensors demonstrated a better performance, in terms of both step detection and orientation.

2.5.2. Filters

Another tracking approach is the utilization of filters, such as the particle filter (PF) and Kalman filter (KF). A PF utilizes a set of particles (samples) for representing the posterior distribution of some stochastic or random process [65]. Each particle represents a discrete state hypothesis of the state variable, and the set of all particles determine the final state estimation. The Bayesian state estimate is an example of PFs and utilizes the discrete particles for approximating the posterior distribution of the estimated state. Another example are the Monte Carlo (MC) methods, which were initially used for the localization of robots. The robot's position and orientation are estimated as it moves and senses the environment and each particle represents a possible state, which is a possible position of the robot. In MC methods, the robot's initial state is unknown, and it begins with a uniform random distribution of particles; thus, it is equally likely to be at any point in the space. Based on the robot's movements, the particles are shifted, so the new state can be predicted and a correlation with the actual one is made.

Alternatively, the KF produces estimates of hidden variables based on inaccurate and uncertain measurements and predicts the future system state, based on the previous estimations. For instance, the hidden variables of the GPS receiver include the location and velocity, and the measurements include the satellite signal's arrivals. Additionally, in [66], the fingerprinting, together with KF, was used for enhancing the RSS estimations, leading to the result that the nearest neighbour estimates were shifted closer to the actual path. Moreover, the KF is based on linear dynamical systems in the state space format; therefore, the process and measurement models are assumed to be linear. For non-linear dynamic models, the extended Kalman filter (EKF) and unscented Kalman filter (UKF) can be used instead. The EKF was used in [40] for fusing the nonlinear RSSI and CSI ranging models for estimating the distance between the receiver and transmitter. It was used to filter the obtained RSSI and CSI values at each reference point, which were then combined with a distance-related mathematical ranging model for reducing the impact of noise on the system and improving the ranging accuracy. A 1.5 m distance error for over 70% of the reference points was reported for the tested indoor environment, together with rich multipath effects suppression.

2.5.3. Simultaneous Localization and Mapping (SLAM) Algorithm

The SLAM algorithm is the process by which the robot (mobile node) can build a map of the environment and simultaneously determine its position on the map. The trajectory of the platform and the location of all landmarks are estimated in real time, without any a priori knowledge. The mobile nodes are sensors with time-varying states, such as position and pose, and the landmarks have fixed or slowly changing states. Specifically, the probabilistic SLAM involves the estimation of an appropriate representation for the observation and motion model, which allows for efficient and consistent computation of the prior and posterior distribution. The observation model is given by:

$$P(x_k, m | Z_{0:k}, U_{0:k}, x_0), \tag{25}$$

where x_k is the state vector, m is the landmark vector, $Z_{0:k}$ is the set of all landmark observations, $U_{0:k}$ is the history of control inputs, and x_0 is the robot's initial state. The motion model is given by

$$P(z_k, m | x_k, m), \tag{26}$$

where z_k is the landmark observation at time instant k, and m is the landmark vector. In SLAM, the correlations between landmark estimates improve and never diverge, so the joint probability density on all landmarks is proportional to the number of observations. For instance, the robot vacuum cleaners, which are used to randomly clean floors, utilize the SLAM tracking, while the newer versions operate in a much more intelligent approach using the vision simultaneous localization and mapping (VSLAM). In VSLAM, the infrared cameras are also used for taking snapshots of the area for building the whole picture of the environment. By "remembering" the layout of the different rooms, future cleaning becomes more effective [67]. Nevertheless, the tracking camera is sensitive to light strength changes [59]. In addition, SLAM can improve the accuracy of the position estimations by using the inertial measurement unit (IMU). The IMU reduces the cost of the system at the expense of increasing the computational complexity and limiting applicability to the particular area/environment used [8]. The IMU-SLAM can be used for pedestrian tracking in indoor navigation, which is useful in emergency scenarios, such as terrorist attacks or buildings on fire. For instance, in [68], the IMU-SLAM was effectively used by the "FeetSLAM" algorithm, which is a collaborative SLAM technique operating in

GNSS-denied and infrastructure-less indoor areas. In particular, the inertial data were derived from the 3D accelerometer and gyroscope and combined with UKF for estimating the pedestrian orientation.

3. Wireless Technologies

The wireless technologies are used for providing the communication medium between entities over distances without the use of wires. Although they were initially intended for replacing the cabling and wiring for mobility and cost-savings, over the last few decades they became a powerful tool for information sharing, productivity, flexible lifestyle, and mobility, as well as a medium for the IoT. In this section, numerous wireless technologies are presented and discussed, with respect to localization. In particular, wide area network technologies, including satellite, cellular, RADAR, FM, LoRa, and SigFox, are presented first, followed by smaller range and lower power technologies, such as Wi-Fi, Bluetooth, UWB, geomagnetism, vision technology, VLC, RFID, acoustic, ultrasound, and infrared radiation.

3.1. Global Navigation Satellite System (GNSS)

The GNSS can greatly facilitate localization outdoors, as long as LoS exists between a few of the satellites and the receiver. The GNSS consists of four positioning systems, the GPS by the USA, GALILEO by the European Union (EU), GLONASS by Russia, and BeiDou by China. In general, the GNSS localization system employs propagation time estimations, followed by the trilateration localization technique. Therefore, LoS with at least three satellites is required, which can be problematic for indoors, dense urban, and underground environments [69]. In particular, the unknown receiver's position is estimated by using the Earth-based coordinate system, which includes the latitude, longitude, and altitude. Each satellite transmits a unique code, and an identical copy is created at the receiver's side. It includes two carrier waves in the L-Band with frequency range from 1530 MHz to 2.7 GHz, together with the satellite's precise orbit details and a very stable time stamp created by an atomic clock, called ephemeris data [69]. The atomic clock is also used for various other navigation and timing services on the global basis. In what follows, complementary GNSS technologies, which aim to address the GNSS limitations, are presented, including indoor localization.

3.1.1. Assisted Global Positioning System (AGPS)

An alternative solution for utilizing the GPS under NLoS or poor satellite coverage conditions, is the assisted global positioning system (AGPS), shown in Figure 12. It aims to improve the GPS performance by using the cellular radio network. The AGPS receivers obtain information via the cellular radio network, which improves the time-to-first-fix (TTFF), at the expense of higher power consumption and processing time [70]. It is extensively used for the emergency numbers 112 (Europe) and 911 (USA) requirement, thus making the cellular phone location data available for the emergency call dispatchers.

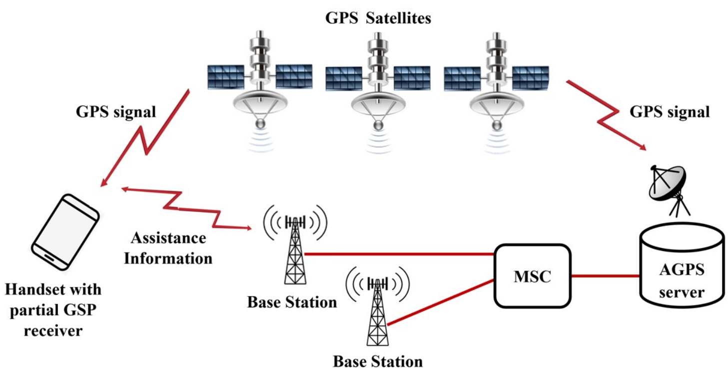
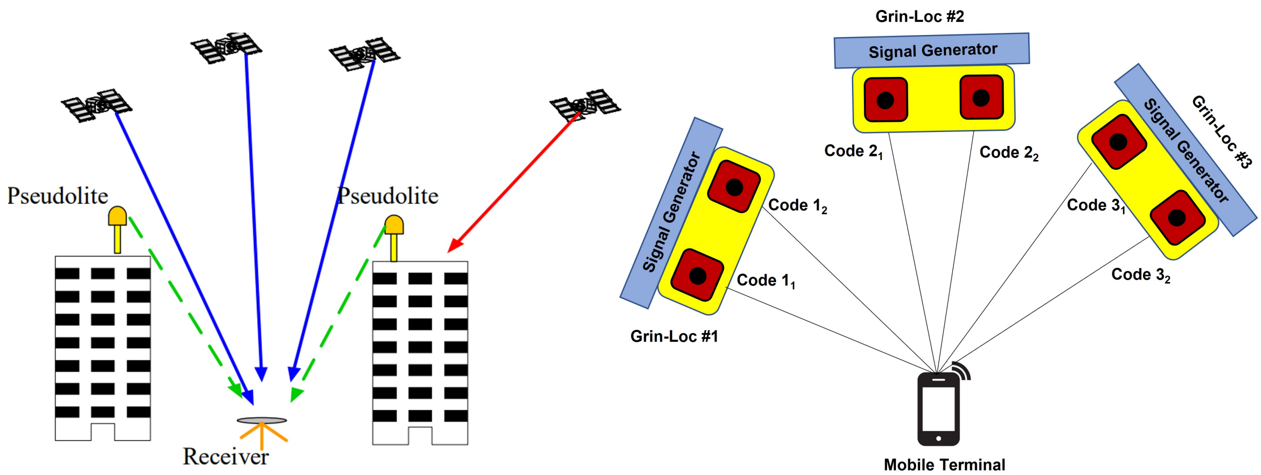


Figure 12. Assisted GPS (AGPS), reproduced with permission from Djuknic, Geolocation and Assisted GPS, published by IEEE, 2001.

3.1.2. Indoor GNSS Satellites

The indoor GNSS satellites aim to utilize the GNSS signals indoors, by assuming that they are always present with lower power signals, compared to outdoors; therefore, very sensitive receivers can be deployed for capturing and retransmitting them [70]. The indoor GNSS satellites include (i) Pseudolites, (ii) Repeaters, (iii) Repealites, and (iv) Grin-Locs, which are detailed below.

Pseudolites are pseudo-satellites, and thus, small in size transceivers, acting as noise code generators for generating local, ground-based GNSS signals [71], as shown in Figure 13a.They broadcast their own signal structure, which includes the GPS frequencies L1 (1575.42 MHz) and L2 (1227.6 MHz). Similar to GPS, they suffer from multipath, near-far problems, as well as time synchronization issues. For instance, in [72], the positioning system utilizes at least four visible satellites without timing and relies on the navigation signal simulator and pseudolites. For diminishing the near-far effect on the receiver, pseudolite antennas that matched the GPS satellite number were deployed. The drawback of this system is the assumption that the information stored in the pseudolites is identical to the actual orbiting satellite; therefore, a range of errors arise.



(**a**) (**b**)

Figure 13. Indoor GNSS Satellites: (**a**) Pseudolites reproduced with permission from Fang-Shii Ning, *Preliminary Testing of Pseudolite to Improve GPS Precision*, published by ResearchGate, 2004, and (**b**) Grin-Locs-based positioning system, reproduced with permission from Samama, *A GNSS-based Inverted Radar for Carrier Phase Absolute Indoor Positioning Purposes*, published by IEEE, 2016.

Repeaters are used to re-broadcast the signals of the outdoor constellation indoors. A repeater is an RF switching device, which receives the outdoor signals and switches them among the multiple re-radiation antennas, one at a time. Its operation includes boosting the reception by using a reception antenna, a signal amplifier, and internal rebroadcast antennas. It consists of two antennas, the active and passive, which are connected with a direct current (DC) power, supplied directly via a coaxial cable. The active is deployed outdoors and contains a low noise amplifier, whereas the passive antenna is deployed indoors and re-radiates the signals. In [73], two scenarios were evaluated, the direct and repeater setup. The direct setup includes a direct connection of the GNSS receiver to an outdoor antenna, whereas the repeater setup includes the GNSS repeater attached to an outdoor antenna, which relays the signals to the GNSS receiver. It was concluded that the TTFF for the repeater setup scenario had a lower TTFF median time, compared to the direct connection scenario. On the other hand, the repeater scenario resulted in the introduction of additional noise and, thus, a lower carrier-to-noise ratio. The technical issues raised from using TDoA measurements for the indoor repeater-based positioning system are also discussed in [74].

Repealites are terrestrial transmitters acting as a satellite and broadcast the signal of the outdoor constellation indoors. In essence, a repealite-based system is a combination of pseudolites and repeaters. They use a single GNSS signal transmitted by the indoor antenna, and the different signals received from the different repealites are distinguished by adding a specific delay to each one. For instance, the system in [75] consists of three repealites, which are evaluated for the carrier phase ambiguities. The carrier phase ambiguities were estimated using the code measurements with a binary phase shift keying modulation applied to the carrier or by gathering information from the environment (i.e., code, carrier phase, and relative signal strength), aiming to eliminate the problems associated with the code measurements. It was concluded that the information from the environment approach provided better accuracy [75].

Grin-Locs, shown in Figure 13b, are characterised by their ability to carry out absolute positioning by only utilizing the carrier phase measurements. The Grin-Locs transmitters are not time synchronized, and two or three transmitters are required for the 2D or 3D space, respectively. Each Grin-Loc transmitter consists of two antennas, located one wavelength (λ) apart and are fed by synchronized signals, each containing a specific code on the same carrier frequency generated locally. The one wavelength is used for obtaining a non-ambiguous measurement at the receiving node, and the two Grin-Locs emit on two frequencies are used for eliminating the near-far problem. The Grin-Loc positioning principle lies on the differences in phase of the measurements for every Grin-Loc. The AoA of the signal on the receiver's antenna and the hyperbola on which the receiver is lying are used for the position estimation. For the AoA, two antennas at the unknown receiving node's side are required, and an approximation is made by assuming that the angle in the middle of the two antennas is identical to the angles from each antenna towards the receiving node. This assumption is exact when the receiving node is located an infinite distance away from the two antennas and satisfactory when the distance between the antennas and the receiving node is greater than 10 times the spacing between the antennas (typically 10λ, thus, 2 m). The system in [76] was evaluated using standard receivers and aiming to estimate the distributions of the error in the measurement of the phase of the carrier. The distributions were then used to predict the precision of the positioning. The guided and the free space setup were evaluated. The receiving node was connected using a coaxial cable to the signal simulator in the guided setup, whereas in the free space setup, the receiving node was equipped with a receiving antenna connected through free space propagation to the signal simulator. The guided setup was shown to outperform the free space setup [76].

3.2. Cellular

The cellular technologies consist of distributed cells and the receivers are served by at least one fixed location transceiver. Each cell utilizes a different set of frequencies, aiming to reduce interference and provide guaranteed quality of service. The cellular-based technologies are commonly used for transmitting voice, data, and multimedia.

3.2.1. Global System for Mobile (GSM) Communications

The GSM is a standard developed by the European Telecommunication Standards Institute (ETSI), which describes the protocols for the different digital cellular networks generations, i.e., 2G, 3G, 4G, 5G, and 6G. Different regions utilize different frequencies, such as the 850 MHz, 900 MHz, 1800 MHz, and 1900 MHz bands, with a channel separation of 200 kHz, as well as constant envelope modulation and carrying traffic channels, according to the time division multiple access (TDMA) principle [77]. It operates in the licensed bands, so interference is prevented with other devices. GSM can be used with three positioning techniques, i.e., the GSM fingerprinting, range-based, and angle-based positioning [20].

3.2.2. Narrowband-Internet of Things (NB-IoT)

The NB-IoT is a low-power wide-area network (LPWAN) technology, introduced by the Third Generation Partnership Project (3GPP) in 2016. It has the advantage of being compatible with the traditional cellular networks and operates at the 200 kHz GSM carrier. Basically, it operates within a small portion of the existing network and available spectrum and is deployed inside the long-term evolution (LTE) carrier, a pioneer technology towards building the 5G. NB-IoT supports the ultra-low end IoT applications for real-time implementations. It also features more than 10 years of battery life and huge data collection capabilities from massive sensors for achieving a smarter way of living. It aims to support more than 50 k connections per cell [11], with high coverage. Through the NB-IoT, enhanced mobile broadband (eMBB) is achieved, which provides accessibility of mobile broadband services everywhere and anytime with extended coverage. Moreover, the NB-IoT utilizes the observed time difference of arrival (OTDoA); thus, several synchronized base stations (BSs) transmit position reference signals (PRSs) to the receivers. The receivers forward the ToA per transmitting BS, together with the PRS, to a localization server for processing and estimating their location [11]. The OFDM is also supported by the NB-IoT technology; therefore, the CSI estimations can be extracted and used for fingerprinting-based indoor localization. In [46], the inverse fast Fourier transform (IFFT) was used for excluding the multipath interference, together with the fingerprinting technique for identifying the LoS paths, followed by the CSI measurements for the position estimation.

3.2.3. Fifth Generation (5G)

The fifth generation (5G) is the latest established global cellular technology. It aims to introduce advanced key technologies with much higher system capacity, spectrum efficiency, energy efficiency, and transmission data rates. It also aims to address the different limitations of previous generations and be a potential key enabler for future IoT. Moreover, it aims to improve the positioning, with the ultimate goal of providing 6D positioning, i.e., 3D spatial location with roll, pitch, and yaw positioning, which is needed for virtual and augmented reality technologies [10]. The prerequisite is for the receiving node to be equipped with an antenna array, so that both AoA and AoD can be estimated simultaneously in either the uplink or the downlink modes [78].

The 5G utilizes high directional antenna arrays with narrow and wide bandwidths for more accurate localization. It also utilizes the mmWave frequency band with large antenna array deployment at both ends. Although the mmWave frequency band suffers from higher path loss in the first meter of propagation and greater blockage, it is expected to achieve a positioning accuracy of less than 1m for indoors and dense urban areas, due to the ultra-wide bandwidths available [79]. The mmWave and THz bands are affected by the weather conditions. In [80], the mmWave and THz bands wireless link budgets were evaluated under extreme weather conditions, such as storms, which include a combination of high temperature, violent rain, and strong winds. It was found that only the 400 GHz carrier was relatively sensitive to severe wind effects, while the link performance was affected regardless of the carrier frequency.

Furthermore, the narrower half-power beamwidth (HPBW) of the antenna arrays allows the AoA of the received signals to be estimated precisely. A finer time resolution of the multipath signals is also provided by the large bandwidths [9]. Moreover, the multi-user *multi-input multi-output (MIMO)* technologies, shown in Figure 14, are utilized in 5G.

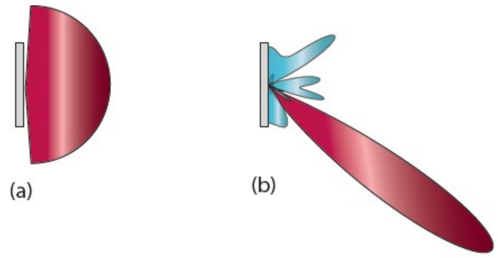


Figure 14. (**a**) A classical antenna, which radiates one signal uniformly, and (**b**) multi-user MIMO antenna, which radiates multiple signals, focused on their respective receivers, reproduced with permission from Björnson, *Massive MIMO is a reality—What is next?: Five promising research directions for antenna arrays*, published by Elsevier, 2019.

They are based on information theory and utilize the properties of an imperfect CSI, as well as AoA estimations for precise signal orientation. MIMO provides the opportunity for exploring the multipath by performing mapping and synchronization [79]. For instance, in [81], numerous snapshots were collected from each base station (BS) and were processed for estimating the location of the unknown receiving node by using the AoA of the LoS paths, under the assumption that there is a LoS path for each BS. Additionally, the massive antenna deployment is included in the 5G technology, which increases the signal strength without changing the radiated power [75]. In [78], an algorithm was developed for coherent passive localization in massive MIMO systems with distributed phased antenna arrays, aiming to solve the ambiguity problem inherent to coherent position estimation.

The 5G technology aims to also provide *massive machine-type communications (mMTC)*, which are predicted to reach tens of billions of connected heterogeneous devices, such as actuators and sensors [10]. The device-to-device (D2D) communication is also introduced in 5G, enabling receiving devices for direct communication with one another and achieving localization of all the receiving devices. Another key network enabler is the cognitive radio (CR) technology, which utilizes the limited and scarce spectrum resources for supporting the high demand of new services requirements of emerging and promising IoT applications. The CR understands the context in which it is located and can tailor the communication process; thus, it is fully aware of the context in which it operates. It is a self-organizing system, in terms of dynamic spectrum access, beam pattern, routing algorithms, coding, and filtering techniques, and aims to reduce the manual configuration and, in turn, provide lower costs. It may be the next generation of cellular networks [10].

Specifically, the 3GPP radio access network (RAN) release 18 enhances the 5G with artificial intelligence and machine learning technologies. The new radio (NR) in release 15 addresses numerous scenarios, such as enhanced mobile broadband (eMBB) and massive machine-type communications (mMTC) and release 16 introduces numerous improvements, such as multiple-input multiple-output (MIMO) and beamforming enhancements, as well as the enhanced support of industrial IoT. Furthermore, in release 17, the multicast and broadcast service (MBS) and non-terrestrial networks (NTNs) are introduced. One of the major improvements in release 18 are the network energy savings, which makes 5G NR significantly more energy efficient, compared to previous generations. It also introduces the conditional handover for the user equipment (UE) receivers. Furthermore, regarding positioning, it was first supported in release 15 and enhanced in release 16 using both downlink-based and uplink-based positioning methods. Additional enhancements for reducing latency for time-critical applications, such as short distance positioning, were included in release 17, while further improvements in accuracy, integrity, and power efficiency were investigated in release 18 [82].

3.2.4. Intelligent Reflecting Surface (IRS)

Intelligent reflecting surface (IRS) is a programmable device that can be used to achieve smart and reconfigurable wireless channels for both 5G and 6G wireless communication systems [83]. It consists of a large number of passive reflecting elements, each of which is capable of inducing a controllable amplitude and phase change to the incident signal independently. This provides the flexibility of reconfiguring the signal propagation between the transmitters and receivers, which, in turn, provides a virtual LoS for bypassing obstacles. IRSs are deployed between the transmitter and receiver channel link and convert the conventional point-to-point direction channel to a channel link between the transmitter and IRS and another channel link between the IRS and receivers [84].

Deep learning can be applied for enhancing the IRS wireless networks, such as estimating the CSI in MIMO communications. For instance, in [85] a deep denoising neural network for mmWave IRS systems was proposed, aiming to estimate the receiver-IRS channel with reduced training overhead. The results showed robustness for a 10 dB SNR. Additionally, in [86] a deep learning approach was used for phase reconfiguration, aiming to learn and utilize the local propagation environment by assuming quasi-static flat-fading channels. It aimed to find the mapping between the received pilot signals and the optimum phase configuration and downlink transmit beamforming vector by capturing important information for the phase and beamforming setting since there is a nonlinear relation between the optimal phases and the channel coefficients. The results showed robustness which makes it possible to apply in different SNR scenarios, without repetitive training.

3.3. Radio Detection and Ranging (RADAR)

The RADAR relies on the radio waves reflected by an object for remotely detecting its presence and speed. Its performance depends on the frequency, polarization, target properties, and distance from the target. The radio waves are commonly affected by dielectric objects, such as the Earth's surface, plants and water. Although it is commercially used for detecting aircraft, ships, spacecraft, etc., its coverage range depends on the minimum received power and visibility (RADAR horizon is defined by the Earth's curvature and the height of the target object). The object range is estimated by the time difference of the echo signal and the corresponding reference. For precise time measurements, various factors must be taken into consideration, such as the pressure and moisture. Additionally, for tracking, RADAR utilizes the Doppler shift, i.e., the change in frequency of a wave, with respect to the observer movement relative to the source. The newer and more advanced RADAR systems utilize MIMO antennas for angle resolution, so the angle-based measurements can also be utilized [87].

Furthermore, the synthetic aperture RADAR (SAR) is used for the Earth remote sensing from airborne and satellite platforms by providing high-resolution 2D images not affected by daylight or weather conditions. Similar to the RADAR system, the SAR satellite transmitted pulse interacts with the Earth surface and only a fraction is back-scattered to the antenna [88]. SAR achieves finer spatial resolution by utilizing the motion of the RADAR antenna over a target region. The resolution is proportional to the size of the antenna aperture and inversely proportional to the distance between the illuminated area and the sensor. Centimeter or even millimeter accuracy can be achieved by comparing two or more complex RADAR images with slightly different positions or acquired at different times [88]. Moreover, the signal strength is affected by the ground properties, the distance between the antenna and ground, and the satellite view angle. Geometric distortions, such as foreshortening, layover, and shadows are also possible, depending on the satellite orbit, configuration, and acquisition parameters [89].

Moreover, the frequency modulation continuous wave RADAR (FMCW RADAR) is a special type of RADAR sensor which radiates continuous transmission power similar to the simple continuous wave RADAR (CW RADAR). Their main difference is that FMCW RADAR can change its operating frequency during the measurement; thus the transmission signal is modulated in frequency or in phase. It is capable of measuring very small ranges to the target, as well as providing very high accuracy of range measurements [90], especially in harsh environments.

In addition, RADARs have a variety of applications, including underwater. The echo sounding, or bathymetry, is the use of sonar for ranging, normally for determining the depth of water, and sound navigation and ranging (SONAR) is commonly used for exploring and mapping the ocean because sound waves travel farther in the water than RADAR and light waves. The multibeam sonar sends out multiple simultaneous sonar beams (or sound waves) at once in a fan-shaped pattern and is used for identifying seafloor types and morphology, whereas the single beam uses only one transducer to map the ocean floor [91].

3.4. Frequency Modulation (FM)

The frequency modulation (FM) is widely used with global coverage for FM radio broadcasting. It encodes the information in a carrier wave by varying the frequency of the wave. It utilizes the very high frequency (VHF) spectrum, which is less affected by weather conditions and obstacles. In fact, FM is very appropriate for outdoor localization, since FM signals are widely available, can travel hundreds of kilometers, can interact with landscapes and environmental dynamics, and can still be effective.

For indoors applications, a year-long experiment, performed in [92], evaluated the ambient FM radio signals by analyzing the robustness of the FM signal features to human presence and weather conditions. It was concluded that ambient FM radio signals were barely affected; therefore, they are suitable for both standalone and hybrid positioning solutions. In particular, FM was compared with Wi-Fi for localization using the fingerprinting technique, and it was concluded that the FM RSS values at a given frequency did not change dramatically over time, whereas the Wi-Fi RSSI signatures were affected the most by temporal variations, causing the localization accuracy to decrease. In addition, the combination of the two provided higher localization accuracy, compared to Wi-Fi alone. Therefore, the combination of the FM and Wi-Fi-based approaches may lead to a hybrid positioning solution in the future.

3.5. Long Range (LoRa)

The long range (LoRa), as the name implies, is a proprietary long-range wide area wireless communication technology with a coverage range of up to 3 km in suburban areas with dense residential dwellings, as evaluated in [93]. LoRa operates in the unlicensed ISM band and is a physical layer protocol, suitable for low power, low throughput, and long-range network applications, like the IoT. It is based on the LoRaWAN, an open standard media access control (MAC) layer protocol that adds a network layer for network congestion handling between the end and central nodes [10]. LoRa utilizes the star-to-star network topology, in which the packets are forwarded by the gateways from the nodes to the network server. The chip spread spectrum (CSS) protocol is used for modulation with different bandwidths, which spread the signal over a wider channel bandwidth. The utilization of CSS reduces the interference from other signals, protects the signal against jamming, and cancels out multipathing and fading effects [10]. Moreover, the number of chirps determine the spreading factor, i.e., a high spreading factor achieves long distances and low data rates, whereas a low spreading factor shorter distances with high data rates. LoRa can achieve localization with TDoA and ToF measurements, due to the higher bandwidth provided [6].

3.6. SigFox

Similar to LoRa, the SigFox is a low-power wide area network (LPWAN) technology and provides a complete end-to-end connectivity solution based on ultra-narrowband (UNB) technologies with a coverage of more than 1000 m [10]. The SigFox coverage area ranges from 30 to 50 km in rural areas, and from 3 to 10 km in urban areas, while it is susceptible to interference from other networks existing in the unlicensed ISM band. It can be offered as a cellular network variation, which enables mobile devices to connect to different BSs with UNB. Similar to LoRa, SigFox is suitable for the IoT, due to its long battery life, low device cost, high network capacity, and long range. The low power consumption is achieved by utilizing the duty cycles; thus, a wireless node wakes up and transmits, then waits, listens for a short duration, and returns to sleep mode [93].

In fact, SigFox is an Internet protocol with no time synchronization requirements. In more detail, the SigFox BSs detect, demodulate, and send the message to the SigFox cloud, a client-server backend that can be accessed by an end user or through application program interfaces (APIs), which are programmed to handle specific data from the SigFox cloud data server. The network messages are sent multiple times on random frequency channels aiming to improve the likelihood of successful reception. Similarly, the end-devices' messages are received by multiple BSs, which provides the opportunity for applying the angulation or lateration localization techniques. Furthermore, the RSS measurements can easily be collected, since they are included in the network messages. The "Atlas Native" [94] is the first system that offers the SigFox location service, solely based on the SigFox network location, aiming to provide the geographic coordinates (latitude/longitude). It consists of a SigFox cloud platform, which receives the different frame replicas, which are then transferred to the geomodule, and the node's location is estimated.

3.7. Wireless Fidelity (Wi-Fi)

The Wi-Fi, also referred to as WLAN, has experienced a rapid growth and increasing popularity over the last few decades. Its wide availability, flexibility, and mobility, with free public Wi-Fi hotspots available almost everywhere with no additional hardware requirements, made Wi-Fi one of the most popular and well-known wireless technologies today [2,12]. This ubiquitous availability also made Wi-Fi the mainstream technology reported in the related literature for indoor localization. It operates on the 2.4 GHz and 5 GHz in the unlicensed ISM band, with up to 1 km coverage, which can be extended through hotspots. Although it was initially intended for computer-to-computer interconnection, nowadays it provides Internet connectivity at broadband speeds. It is based on the IEEE 802.11 standard, which specifies the set of MAC and physical layer (PHY) protocols for implementing WLAN communication, as well as the compatible interconnection of data communication, using the carrier sense multiple access protocol with collision avoidance (CSMA/CA). Numerous amendments, such as 802.11 g and 802.11 n, have been introduced, which mainly define the frequency band, bandwidth, and transmission rates. Although it is capable of operating in NLoS and not sensitive to lighting conditions, it suffers from high power consumption, compared to other WLAN technologies.

The RSS measurements are the most commonly used measurements for localization, and they are affected by the free-space loss and large-scale attenuation caused by obstacles, even for small wavelengths, i.e., λ = 12.5 cm [95]. While, the time-based measurements are less commonly used due to the complexity of measuring the time delays and angular information [20]. Moreover, fingerprinting is the most commonly used localization technique, due to its wide availability and ability for building self-constructed databases. For instance, the "Locate me" [96] contains databases that are calibrated by adding users' personal places and mobile calls. It combines the Wi-Fi and GPS technologies for providing an indoor/outdoor localization system. The algorithm requires at least three Wi-Fi APs, which are matched with the location database, and the output is provided on a website to be used by the users. Moreover, "Chronos" [97] utilizes a single Wi-Fi AP and combines the information across different Wi-Fi channels for achieving fine grain resolution, similar to UWB.

Another Wi-Fi localization approach is by "network sniffing", with the utilization of the packet information, such as the probe requests and probe responses. More specifically, the packets exchanged during discovery, i.e., while a receiving node (station) is searching for the available transmitting nodes (APs) within its range, contain probe requests from the station to the APs, and probe responses from the APs to the station. The additional information exchanged include the device's unique MAC address and timestamp. This method can only be used with older smart devices, since the newly released operating systems (OS) adapted the randomized MAC addresses feature; therefore, the tracking and localization is more difficult and sometimes impossible. Nevertheless, this technique was also used maliciously for stealing sensitive information, such as passwords. The "HuMAn" system [98] utilized the network sniffing method by combining the RSS measurements, together with the fingerprinting localization technique. The RSS measurements were collected and processed for training, aiming to make localization predictions.

Furthermore, some Wi-Fi amendments support the FTM protocol, which provides fine-time measurements, so time-based, i.e., RTT measurements, localization techniques can be used. For example, in [99], the FTM protocol measurements and the trilateration technique are used. Although the system achieved meter-level accuracy, it was significantly affected by the NLoS conditions. In addition, the combination of time-based and RSS measurements can be used, such as in the "WiNar" system [30], which utilizes the RTT and RSS as fingerprinting features, aiming to address challenges of the indoor environment, such as multipath, NLoS signal attenuation, and interference. It was concluded that the average localization error for both scenarios, RTT only and hybrid RTT-RSS, was almost the same. Likewise, in [34], RTT-based ranging was found to accurately reflect the true distance between the stations and the APs for both LoS and NLoS conditions.

3.8. ZigBee

The ZigBee technology specifies the PHY and MAC layers and is based on the IEEE 802.15.4 standard, which adds the network (NWK) and application layer (APL) specifications on top of it to complete the full ZigBee stack [100], as shown in Figure 15.

ZigBee operates in the unlicensed ISM band at 2.4 GHz, offers data rates up to 250 kbits [93], and supports simple devices with minimal power operating in the personal operating space (POS) of 10m. It also provides self-organized, multi-hop and reliable mesh networking with long battery lifetime. ZigBee networks consist of three types of nodes, the gateway, static, and mobile nodes. The gateway is used for interconnecting the network to another node or network, the static nodes are deployed in known locations and act as reference nodes, and the mobile nodes are the ones that need to be localized. The mobile nodes are usually worn or carried by people, have lower computational capabilities, and are incapable of performing any network-related services.

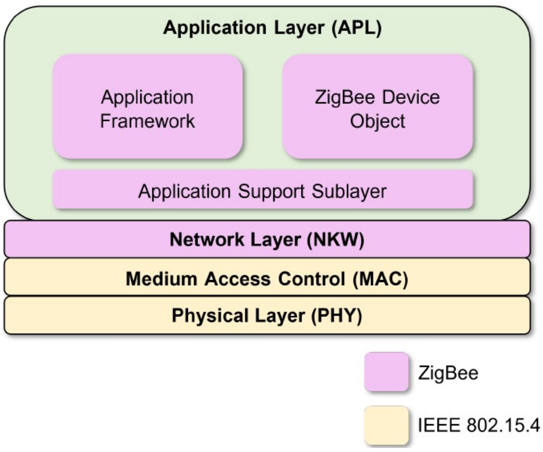


Figure 15. ZigBee stack reproduced with permission from Li, *Research and Application of ZigBee Protocol Stack*, published by IEEE, 2010.

For instance, the ZigBee indoor monitoring system in [100] is based on RSSI measurements and aims at helping the school authorities keep track of children in school premises and even locate teachers in case of an emergency. The localization algorithm consists of the collection of the raw RSSI measurements, followed by the deterministic phase (calibration) and probabilistic phase (smoothing). Finally, the position is estimated by iterative trilateration. The mobile nodes were embedded in the students' and teachers' ID cards. The gateway was configured to periodically broadcast messages to the static nodes for updating the network information. Compared to LoRa, the ZigBee network is established using a single static channel for communication, so is more susceptible to interference. Another ZigBee weakness is its inability to communicate with smart devices directly, without additional hardware.

3.9. Bluetooth

The classical Bluetooth technology is based on the IEEE 802.15.1 standard and is used for ad hoc communications. Similar to LoRa, SigFox, Wi-Fi, and ZigBee, Bluetooth operates in the unlicensed ISM band, with low-power, low-cost transceivers, and is designed for peer-to-peer communications. It was originally intended for replacing the wired communication between devices, with effective high data rates for audio and data streaming applications. It is a LPLAN technology with range coverage of less than 1000 m, which is divided into three classes, class 1 up to 100 m, class 2 up to 10 m, and class 3 up to 5 m [24]. Nevertheless, the majority of the Bluetooth devices operate in class 3. Compared to Wi-Fi, Bluetooth is widely available and embedded in almost every smart device, while it has a lower bit rate and a shorter transmission distance [20]. Bluetooth limitations include the restriction to one-to-one communication [10] and latency issues caused during the device discovery.

The Bluetooth low energy (BLE), also called Bluetooth 4.0 [10], was introduced in 2011 as an extension featuring low energy and low transmission power [101]. It is the successor of the classic Bluetooth and operates on the unlicensed ISM spectrum band with a maximum signal range determined by the transmission power [25]. It divides the spectrum into 40 channels, 3 of them are dedicated for advertisements, which are connectionless and broadcast their signals periodically, and the rest are for data exchange. Compared to the classic Bluetooth, the BLE reduced the number of channels for preventing the signals from overlapping with other technologies. The low-cost BLE beacons (receivers) are powered by coin cell batteries, operating for several years without replacement [101]. BLE has shorter coverage and, compared to Wi-Fi, is more suitable for power constrained applications, such as the IoT. Compared to the classic Bluetooth, BLE supports one-to-many connections and periodically, within an advertising interval, broadcasts short packets. These packets are received by the BLE beacons and can be used for estimating their position, i.e., using the RSS measurements. The trilateration and fingerprinting localization algorithms are commonly used for BLE positioning.

For instance, in [43], the BLE trilateration-based location tracking system utilized a smartphone's RSS measurements, which were analysed, and the closest BLE AP was selected as a reference point. Additionally, the smartphone's accelerometer sensor was used for detecting the pedestrian's movements, and the location tracking error was evaluated by touching a button on a smartphone application when approaching each BLE AP. It achieved an average location tracking error of 3.01 m, which was slightly decreased by applying the Kalman filter. Additionally, the iBeacon and Eddystone, introduced by Apple in 2013 and Google in 2015, respectively, are among the most popular IoT BLE beacons [3,25]. BLE beacon-based localization systems are also used in real-world environments, such as in the Gatwick International Airport, where, combined with augmented reality technology, they are used to aid passengers in navigating unfamiliar places, i.e., locating the check areas, departure gates, and baggage belts [25].

3.10. Ultrawide Band (UWB) Technology

The UWB is a short-range, low-power wireless technology that utilizes a sub-nanosecond radio pulse and transmits data in a wide bandwidth for strong multipath resistance and high precision [27]. It transmits short pulses, less than 1ns over a large bandwidth, so higher accuracy between 20–30 cm can be achieved [2]. Although it can penetrate walls and resolve the multipath problem, its accuracy is significantly degraded when operating indoors [102]. In addition, the UWB hardware is expensive, so it is considered a high cost technology for wide scale applications [20]. Compared to Wi-Fi, the UWB availability is limited to only some smartphones [103].

In [102], three commercial UWB-based localization systems using TDoA and AoA measurements, "Ubinense", "BeSpoon", and "DecaWave", were evaluated in a big industrial warehouse with diverse obstacles causing propagation loss and diffraction on the UWB radio signals. The Gaussian and Gamma distributions were also used for modeling the LoS and NLoS conditions, respectively, as well as a particle filter for updating the implementation of the non-normalized distribution function. It was concluded that, under NLoS conditions, the "BeSpoon" was slightly better than "Decaware" and significantly more reliable than "Ubinense", whereas under LoS conditions, the "Decaware" was more accurate, compared to "DeSpoon", since "Decaware" uses more advanced antennas. Regarding the measurements, the AoA measurements were more informative and accurate, with fewer outliers compared to TDoA measurements. Overall, the "Decaware" was found to be superior to both "DeSpoon" and "Ubinense".

3.11. Geomagnetism

The geomagnetism covers all aspects of the Earth's magnetic field and can be used in INS (see Figure 10) for providing the absolute heading estimation. The heading can be expressed as a vector and used for determining the direction of the azimuth, i.e., the magnetic North, using a compass. The local magnetic field anomalies can be used as fingerprints for distinguishing the different locations [104]. The advantage of the geomagnetism is that no additional infrastructure is required and a geomagnetic map can be created.

In [104], a geomagnetic map was created using the accelerometer and gyroscope aiming to enhance the feature vector by estimating the different orientations. The database consisted of the raw data collection from the accelerometer, gyroscope, and magnetometer sensors. Furthermore, in [105], a combination of magnetic, acceleration, and gyroscope quaternion (MAGYQ)-based attitude angles estimation filter was used with dynamic and static motion conditions. The MAGYQ was evaluated in both indoors and outdoors, with three people walking at a normal pace. For the outdoor environment, the GNSS was used to obtain the ground truth, while for indoors, the different footpaths were overlayed on the building background map. Similarly, in [106], the ambient magnetic field was used on a smartphone for identifying different anomalies, which can be used in machine learning-based classifiers and distinguish the indoor and outdoor environment. Furthermore, magnetic maps [107] can be created by utilizing the smartphone's magnetometer for collecting data measurements. The magnetic maps can be used for improving the existing visual maps for location tracking and navigation purposes.

3.12. Vision Positioning Systems (VPS)

The vision technology mainly utilizes a camera or other scanning devices for distinguishing different characteristics in the environment. Vision positioning systems (VPS) aim to match real-time images with stored frames or pre-constructed models, for relative or global pose estimation. Although it is a widely available technology with no additional infrastructure required, high storage capacity is still needed for building the images' database annotated with the environment map [24]. Moreover, the camera should be used at a low transmission rate, so the target must be stationary or slow moving [44].

For localization purposes, it can offer submeter accuracy; however, it is easily affected by the pose and orientation of small devices, as well as the latency caused by the real-time communication between the server and smart devices. Specifically, a small change in the camera angle may significantly change the captured image, which can potentially influence the localization performance. This can be eliminated by adding the camera angle and orientation in the database and matching them with the captured images, which requires high storage capacity. The fingerprinting technique is commonly used for the image analysis and relies on the camera acquired images, segmented to extract features and estimate the closest match of extracted features against the database features. The feature extraction involves the processing of an image for extracting a set of numerical values, which can uniquely describe the image [24]. During the fingerprinting online phase, the image similarities are identified by decoding their transmission identifiers for their location [26].

For instance, the perspective-n-point (PnP) pose problem [108] aims to estimate the relative pose, i.e., 3D position and orientation between a calibrated camera and 3D object, or the entire 3D scene, from a set of n visible 3D points with known scene coordinates and their 2D projections with known pixel coordinates [109]. Therefore, the geometric relations between the object's 3D coordinates and their 2D projection coordinates on the image sensors can be used to determine the position [108]. Additionally, the VPS can provide useful information based on the captured images or by using 2D tags, such as barcodes with encoding information, recorded and processed by a smart device with built-in cameras. For instance, Google maps navigation can provide visual guidance; thus, the users can spot their surroundings using their smart device's camera and visually interpret their direction with great accuracy [110].

3.13. Visible Light Communication (VLC)

The VLC is defined as the unguided optical transmission by using light emitting diodes (LEDs) or fluorescent lamps. It is a solid-state lighting technology in which data can be encoded in the emitting light to realise communication [26]. LEDs can be easily modulated [111], with higher Lumina's efficiency, low power consumption, low-cost, long lifetime, and fast speed response. Their fast switching, which remains imperceptible by human eyes, changes the light intensity and enables data encoding [15,112]. Moreover, the high data transfer and enhanced security makes the VLC a complementary solution for the ubiquitous RF-based wireless communication [15]. It is, in fact, a good alternative solution for RF-sensitive places, such as hospitals and aircraft, with a short transmission range communication capable of distinguishing different enclosed areas in indoor settings. Its narrow bandwidth provides the opportunity for AoA measurements to be used for localization at the receiver's side. While it is less affected by multipath interference, when compared to RF technologies, it is affected by shadowing and body reflections, especially in the case of brightly coloured clothing [15]. The fingerprinting can also be utilized, since the light strength is stable at different times of the day.

The VLC localization system, shown in Figure 16, typically consists of the LED transmitting nodes, the receiving node (e.g., smartphone) whose position needs to be estimated and the channel.

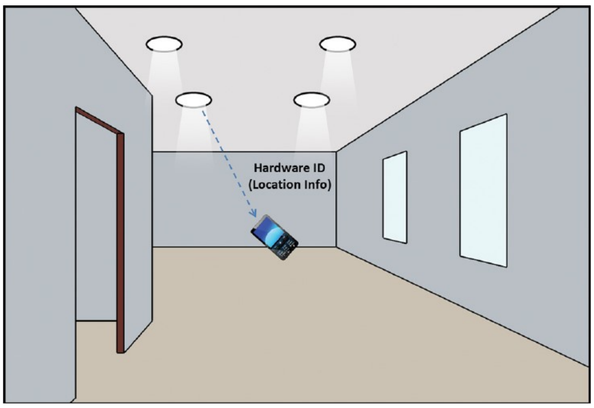


Figure 16. VLC localization system, reproduced with permission from Zhang, *Asynchronous indoor positioning system based on visible light communications*, published by SPIE Digital Library, Optical Engineering, 2014.

Specifically, modified LEDs are deployed on the ceiling and transmit their information related to their physical locations. The commercial LEDs commonly follow the Lambertian radiation pattern [44,113], which is the angular distribution of the escaping light from certain diffuse sources. Moreover, the receiving node must support light detection for analysing the light beacon message. Light detectors include light sensors, photodiodes

(PDs), photodetectors, and the camera's image sensor. The PDs detect and convert the light to photo current, which is proportional to the received optical power on the detection area [114], and provide ToA, RSS, and TDoA measurements. On the other hand, the light sensors require multiplexing design for separating the light signals from the different light sources. Nevertheless, the image sensors are widely deployed on smart devices and can provide AoA measurements. AoA measurements can be used in combination with the RSS for localization and result to small mean localization error, i.e., 0.50 cm [111].

Moreover, a calibrated smartphone rear camera can be used as an optical sensor. For instance, in [108], four uniformly distributed LEDs were deployed on the ceiling and their IDs were decoded from the pixels transmitted from a 10 s real-time video stream. This approach reported mean positioning errors of 4.81 cm and 6.58 cm, at 50 cm and 80 cm heights, respectively. Image sensors can also be used in combination with IMUs, i.e., in [44], the image sensor was used together with a mobile device accelerometer. The accelerator sensor was used for sensing the image sensor tilt, motion, shock, and vibration of the smart device, while the light sensor received the light signals and demodulated the LEDs coordinates. Furthermore, various combinations can be used, such as the TDoA measurements with a single LED transmitter and multiple PDs or the combination of the TDoA and frequency division multiplexing (FDM) [112]. Multiple not time synchronized transmitting nodes can also be used with the basic framed slotted additive link on-line Hawaii system (BFSA-ALOHA) protocol [113]. The on-off-keying (OOK) [26], can also be used as a modulation technique. For simulation evaluations, the OOK signal can be generated by an arbitrary waveform generator (AWG), while the transmission optical channels can be modelled by using the impulse response [115].

Another important parameter is the signal-to-noise ratio (SNR), which estimates the effects of the system. Commonly, the noise is considered to be Gaussian and is estimated as the sum of the contributions from shot and thermal noise. The shot noise is induced by the ambient light, which is proportional to the total light power reaching the PD, whereas the thermal noise is a white noise raised from the system's parts [116]. The SNR can be 10 dB lower in sunlight-exposed room environments, as compared to indirect sunlight exposure [113]. It is also affected by the LEDs' arrangements, i.e., for symmetrical arrangement at the ceiling corners, the SNR is low and the system's performance is downgraded when the user moves far away from the LEDs. From the different configuration arrangements, i.e, circular, square, and hexagonal, the circular arrangement of PDs outperformed the others, in terms of accuracy [112]. For the light sensors, the Skellam distribution [44] can be adapted for determining the overall noise for two consecutive images captured at the same scene.

3.14. Radio Frequency Identification (RFID)

The RFID wireless technology is often used for the identification and tracking of objects by using the RF electromagnetic fields, even under NLoS conditions. Its range can be from centimeters up to tens of meters, and it operates in the unlicensed ISM bands. It is an RF technology, and its accuracy and maximum detectable range are affected by the environment and multipath caused from the NLoS conditions [117]. It is a non-contact wireless technology used for data transferring, and the RFID networks consist of readers and tags. RFID tagged objects are uniquely identified; thus, the RFID technology is suitable for inventory and assets' tracking. In particular, the RFID reader sends a signal to either a passive or active tag, which modifies the signal reflected or retransmitted back. The active RFID tags include a transmitter and their own battery, which is used for broadcasting the signal to the reader, whereas the passive tags have no battery. Tags transmit a response of their internal information, such as a unique ID and RSS information. Typically, passive tags are used as a traditional barcode technology replacement and are lighter and less expensive, as compared to active tags, and they provide unlimited operational lifetime [117]. Generally, the RFID technology includes a wide range of applications, such as pet and livestock tracking, inventory management and control, asset, equipment, and personnel tracking, and entrance control. The warehouse tags are usually deployed on the products' cartons and reflect a signal to a handheld reader for identifying the contents of the product. Additionally, in large organizations, the personnel can "clock in" and "clock out" easily with an RFID key fob or card for accurate time recording, improved payroll accuracy, fairness, and transparency.

Typically, an RFID-based localization system includes an additional data processing subsystem for processing the data received from the RFID readers and executing the localization algorithms, as shown in Figure 17.

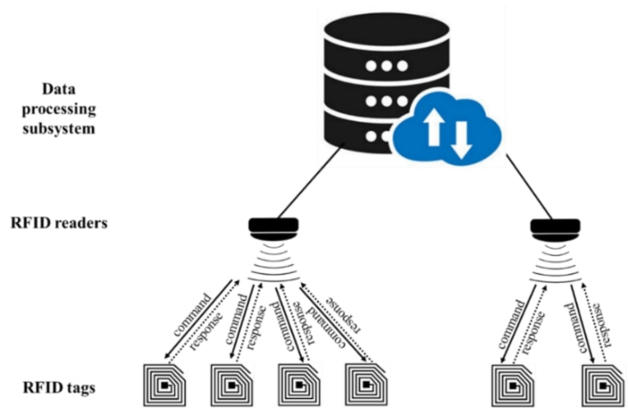


Figure 17. Typical RFID system reproduced with permission from Lionel, *RFID-based Localization and Tracking Technologies*, published by IEEE, 2011.

In particular, the RFID reader interrogates one or more RFID tags for obtaining their unique IDs and retransmits them to the data processing subsystem for further processing. The tags transmit their unique ID signals randomly every 7.5 s on average [117]. By deploying numerous readers acting as transmitters, which receive the RSS information from the same tag, the target location can be estimated at no additional deployment cost [118]. Furthermore, compared to Wi-Fi and BLE technologies, the RFID enables spot localization due to the highly limited range of less than a meter. Although it is a low-cost and easy technology to deploy, it can consist of massive numbers of randomly deployed RFID tags, so message collisions can arise. This can be eliminated by assigning random delays for the various tags' response times, as in the "LANDMARC" [117]. Moreover, the ability of RFID to operate in NLoS and rich multipath conditions is evaluated in [119] by deploying the "PinIt", a commercial RFID system with UHF reference tags.

3.15. Acoustic

An acoustic-based localization system utilizes the sound for determining the distance and direction of an object. The acoustic signals were initially used for detecting aircraft and objects under water by using the sound navigation and ranging (SONAR). Nowadays, they provide another dimension for smart applications, mainly due to the wide availability of microphones, speakers, and audio chips embedded on the smart devices [23]. The acoustic-based localization systems can be classified as active or passive. The former include the creation of sound for producing an echo aiming to determine the target's location, whereas the latter include the detection of sound created by the target. Additional features, such as the energy, temporal, and directional features of the incoming sound at different microphones, can also be used, together with a suitable model for estimating the source location [14]. Additionally, the acoustic-based localization algorithms depend on the speed of sound, which is influenced by variations in temperature and humidity. For instance, a 1 °C offset in the temperature can cause about 0.606 m/s drift in the sound speed, when the humidity is 0% [13].

Beamforming and holography can also be used. Beamforming can identify the sources by scanning all potential locations and holography for making sound fields' predictions.

Similarly, the steered response power (SRP) approach, which is a combination of RSS, ToA, and DoA estimations, can be used. The SRP is a beamforming-based technique that estimates the output power of a filter-and-sum beamformer steered to the source locations defined by a predefined spatial grid. The different SRPs are collected from various points and make up the SRP power maps, and the point with the highest value corresponds to the estimated source location. In asynchronous networks, the SRP power maps are accumulated at the central node, and the combined SRP power map indicates the source location.

Alternatively, the audio playing and recording capabilities of the devices can be utilized. For instance, the wireless acoustic sensor networks (WASNs), which consist of distributed wireless interconnected acoustic-sensing devices equipped with audio playing and recording capabilities, require at least three acoustic nodes for estimating the target's position using the ToA measurements. The WASNs accuracy is proportional to the microphones' density. The "BeepBeep" [33] is a purely software-based solution that utilizes a combination of microphones and speakers. Similarly, the "Beep" [120] employs roaming devices with wireless capabilities.

3.16. Ultrasound

Ultrasound technology is popular in medicine for creating images of the internal body structure. It operates at frequencies above those audible to the human ear. For localization, commonly, the ToF measurements together with the sound velocity are used for estimating the distance between the transmitting and receiving nodes. Although it can obtain an accuracy of sub-centimeters, it has limited maximum range (approximately 10cm) in still air conditions [102], and it cannot penetrate walls. It also suffers from interference resulting from the reflected ultrasound signals from different materials, such as metal [21]. The directional transmission pattern of the ultrasonic pulse is known to be hemispherical, and some orientation information about the receiver can be estimated based on its location and the ultrasonic pulse detected [121].

The ultrasound signals can be also used in combination with RF, as in the "Cricket" system [32]. More specifically, its beacons transmit their IDs and location information through the RF signal. The listeners utilize both the RF and ultrasound pulses for estimating their distance from the beacons. The "Cricket" achieved an accuracy of a few centimeters over ranges of up to ten meters. Similarly, the distributed object locating system for physical-space internetworking (DOLPHIN) [122] utilizes the ultrasound pulse, and the receiving nodes are localized in a distributed manner by using only a few manually configured reference nodes. It is based on a hop-by-hop locating mechanism with LoS; thus, it requires at least three nodes for determining the rest of the nodes' locations in the network, even if the nodes cannot receive ultrasound from the reference nodes directly. The technologies used include the RF for time synchronization and ultrasonic pulses for the TDoA measurements. By the time that an ultrasonic pulse is detected by the receiving nodes, the internal counter stops, and they compute their distance from the transmitting nodes. "DOLPHIN" achieved an accuracy of approximately 15 cm, which was degraded as the hop count between the reference and receiving nodes increased. This principle was also utilized by the "Bat" system [31].

3.17. Infrared Radiation (IR)

The IR is a type of electromagnetic radiation invisible to human eyes and can only be felt as heat. Its name is derived from the electromagnetic spectrum frequencies, since infrared waves occur above microwaves and below the red visible light frequencies [123]. It is widely used for numerous applications, such as remote controls. Additionally, the infrared data association (IrDA) protocol is used for wireless devices and motion detectors. IR is also used for localization systems, such as a moving robot equipped with an IR LED camera, and localized from the reflecting artificial landmarks [124].

An IR-based indoor positioning system was used in [125] for obtaining traffic flow data of pedestrians. The system was evaluated in the passageway of a laboratory and consisted of an IR beacon, a receiver, and a processing unit. The IR beacons transmitted their ID signal using pulse position modulation (PPM) and were attached to shopping bags. The receivers were deployed on the ceiling and measured the angle of incidence of the beacons via a pinhole camera, which was used for estimating the beacon position and identifying the ID signals. The arrival position on the side of the photodiode array changed according to the angle of incidence. A total of 12 photodiodes were used, and the IR beacons were deployed every 0.5 m along the passageway, resulting in a maximum error of 0.7 m.

Passive infrared (PIR) sensors can also be used for detection and localization. The PIR-based localization system's accuracy depends on the sensors' density and their distribution, as well as the intersection of their FoVs. For instance, a grid-based accessibility map was developed in [126] and was subdivided into a finite position grid, in which each grid point provided its location in the environment and the probability of a person being present at that location. The system was evaluated indoors using the people's daily visits. For finding the optimal path from the initial node to the destination node, the A-Star algorithm was used. The PIR data were collected every 0.05 s from each sensor, and the people's locations were estimated. Two different routes were evaluated with mean distance errors of 0.227 m and 0.188 m, respectively.

4. Discussion

Both indoors and outdoors localization systems face numerous challenges. In this section, some of these challenges and future directions are discussed.

4.1. Statistical Analysis

Throughout the presented systematic literature review, a total of 126 scientific papers have been analysed and evaluated, out of which, 67 (53%) are journal articles, 33 (26%) appear in proceedings, and 24 (19%) are surveys/review papers, covering a range of 30 years, i.e., from 1992 to 2022, as shown in Figure 18. As expected, there appears to be an increasing interest from the research community in wireless positioning technologies over the last decade, and especially since 2018, with more than 10 publications per year.

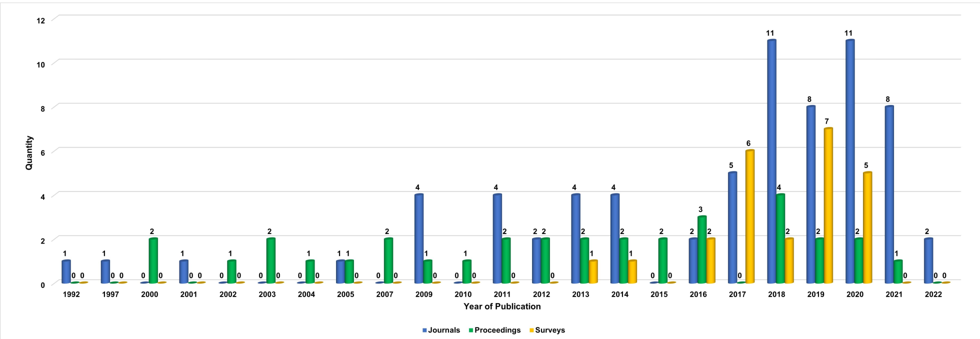


Figure 18. Year of publication for the reviewed literature, of which 67 (53%) are journals, 33 (26%) are proceedings, and 24 (19%) are surveys.

The reviewed literature is further analysed in Figure 19, with respect to (a) the localization technique and (b) the wireless technology employed. Out of the 126 scientific papers, it was observed that the most common localization technique was fingerprinting with 17.46%. In addition, range-based techniques (i.e., lateration and angulation) were used in 19.05% of the reviewed papers, while range-free localization techniques only appeared in 10.32%. Moreover, time-based measurements were the preferred method for position estimation, with 23.81%, followed by angle-based measurements with 19.05% and channel-based with RSS and CSI receiving 16.67% and 8.73%, respectively.

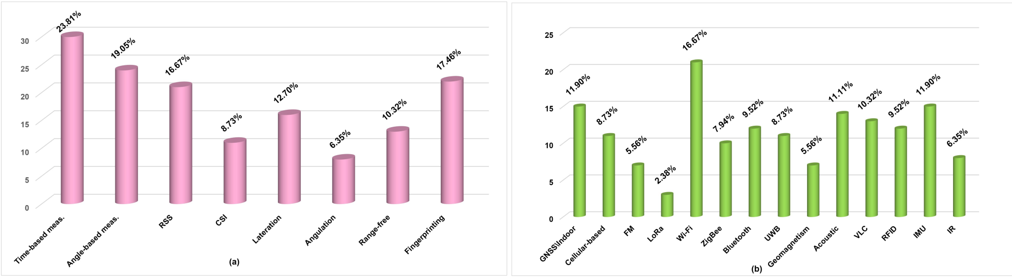


Figure 19. Statistical analysis of the reviewed literature, with respect to: (**a**) Localization techniques, and (**b**) Wireless technologies.

Regarding the wireless technologies, Wi-Fi was the most popular, with 16.67%, followed by GNSS/Indoor and IMU, both with 11.90%, whereas LoRa was the least popular, with 2.38%. A matching between the different localization techniques and wireless technologies in the related literature is shown in Table 3.

Table 3. Matching between the different localization techniques and wireless technologies in the related literature.

	Wireless Technologies												
Techniques *	**GNSS/Indoor**	**FM**	**LoRa**	**Wi-Fi**	**ZigBee**	**Bluetooth**	**RF** ***	**UWB**	**Geomagnetism**	**VLC**	**RFID**	**Acoustic**	**IR**
ToA	[72,73] [74,75]			[97]			[32] [47]	[102]		[113] [116]		[31,32] [33,121]	
TDoA	[74,76] [127]						[122]	[102]		[112] [128]		[122]	
RTT				[30,99]		[101]							
PDoA								[35]					
AoA							[36,37] [78,81] [39]			[115] [129]			
LQI							[39]						
RSS	[71]			[30,34] [66]	[100]		[41,55] [47,51] [49]	[35]		[115] [129]	[117]		
CSI	[46]			[130]							[119]		
Lateration							[48]					[120]	
Hyperbolic	[74,76] [127]						[122]	[102]		[112] [128]		[122]	
Angulation							[36,37] [78,81] [39]			[115] [129]			

Table 3. *Cont.*

	Wireless Technologies												
Techniques *	**GNSS/Indoor**	**FM**	**LoRa**	**Wi-Fi**	**ZigBee**	**Bluetooth**	**RF** ***	**UWB**	**Geomagnetism**	**VLC**	**RFID**	**Acoustic**	**IR**
Fingerprinting	[96]	[92] [95]	[61]	[41,92] [96]	[61]				[104] [107]		[117]		
APIT							[50,53] [54]						
DV-Hop							[51,52]						
MDS							[45,49] [48]						
SNAP							[55]						
PDR/IMU **				[65,66]						[44]			
Filters						[3]			[106]			[131]	[105]
SLAM													[68]

* Distance and position estimation techniques. ** PDR includes the position and orientation estimation algorithms. *** RF includes the scientific papers that did not explicitly specify the wireless technology employed.

4.2. Design Parameters

During the localization system's design phase, numerous parameters must be taken into consideration. The following are some of the most crucial parameters that have been identified from the related literature.

Availability: The hardware availability initiates new possibilities for real-world localization systems and can lead to the wide scale adoption of the related technology. Proprietary hardware makes the localization systems difficult to implement. For instance, VLC and Wi-Fi technologies are widely available, with no additional infrastructure requirements, whereas ultrasound-related implementations require additional infrastructure.

Cost: In general, the localization system's cost can be minimized by avoiding additional hardware requirements and modifications. Nevertheless, the cost is related to the specific application. For instance, low-cost localization systems can enter the consumer market and be widely adopted, while for critical applications, such as emergency response, police, and air traffic control systems, high-cost dedicated hardware with high accuracy are preferred for privacy and safety reasons.

Energy efficiency: Energy efficiency is of vital importance, especially for battery-powered sensors, such as WSNs and IoT devices. Low power wireless technologies, such as BLE [18] and IMU [64], have become widely available and can achieve significant battery savings by entering a sleep mode, while not in data transmission or reception mode. The energy consumption is proportional not only to the transmission power, but also to the computational complexity of the employed localization algorithm. In particular, BLE and UWB technologies utilize low transmission power; however, fusion algorithms can increase the computational complexity of the positioning systems and reduce the battery life. Nevertheless, for WSNs and IoT, localization is an add-on service; therefore, power consumption should be as low as possible. On the other hand, for critical applications, in which the localization and tracking are the main services, such as air and marine traffic monitoring and control systems, energy efficiency is not of fundamental importance. For these cases, systems with uninterruptible power supply (UPS) power protection and private power generators are used instead.

Privacy and security issues: Privacy and security issues should be taken into consideration during the development stage of the positioning systems. Particularly, for localization systems intended for general public use as an add-on service, the privacy rules and regulations of the general data protection regulation (GDPR) [132] should be taken into account, as to avoid jeopardizing the users' privacy and security. However, this important issue has received limited attention so far in the related literature. For instance, in [98], the device owners had no means of noticing that they were being tracked; in [133], the system had been reported to compromise user privacy; while in [96], privacy issues may be raised since users were adding their location in a database. Additionally, for the commercial localization systems, the corresponding rules and regulations should be followed, such as the federal aviation regulations (FARs) and government laws.

Localization and tracking accuracy: Accuracy is the degree to which the estimated position from the localization system conforms to the actual position. Accuracy also depends on the particular application. Some applications require cm level accuracy, while for others, a few meters accuracy is satisfactory. For example, GPS accuracy is acceptable to be within a 4.9 m radius under LoS [19], while other technologies, such as Wi-Fi and 5G, can achieve sub-meter localization accuracy (i.e., [97,134]). It is affected by the environment, such as weather conditions, obstacles, and noise. For commercial localization systems, high accuracy is required; therefore, advanced signal processing and noise elimination techniques are employed, which can be highly challenging tasks.

Fault tolerance: Fault tolerance defines the network's capability for continued uninterrupted operation, despite the failure of one or more nodes. Although it is of vital importance, it is rarely discussed in the existing literature. In particular, only in [55] are the collaborative efforts of the sensor nodes in a WSN promoted for providing a fault-tolerant localization system.

Latency: Latency defines the amount of time required for a packet of data to be captured, processed, and transmitted through multiple devices, until the time it is received and decoded at its final destination. It is proportional to the nodes' density, and it is important for real-time localization systems, which may require milliseconds of response time.

Scalability: Scalability is the ability of a system to continue to function when changes occur, such as additional nodes or demands introduced into the system. In particular, a system can increase or decrease its performance, according to the changes in demands, for instance, by increasing the nodes' density in the network, which increases the coverage area [8].

Real world environment deployment: Both indoors and outdoors environments include various dynamics, such as construction materials, people movements, and weather conditions. A usual assumption in designing localization systems is the existence of at least one LoS path between the nodes, as well as noise-free conditions, which may not always be realistic.

4.3. Future Directions

From the reviewed literature and analysis emerge a number of promising research directions for designing the future wireless positioning systems. In this section, we discuss the fusion of different techniques and technologies, real-world testing and deployment, cloud and edge computing, and new techniques and technologies, from smart sensors to 6G.

4.3.1. Fusion of Different Techniques and Technologies

The combination of different techniques and technologies may provide flexible, powerful, and robust location systems in the future [102]. For example, the RSS and AoA estimations, together with the VLC technology, have been effectively combined for reducing the mean localization error in [129]. Additionally, in [120], the combination of the multilateration localization technique with the acoustic signals provided promising results in the 3D plane. Moreover, the CSI estimations can be utilized with the OFDM standard, as they are more stable in the different environments and can, thus, help maintain the system's performance over time [46].

Although fingerprinting has been widely used in the literature, its usage is limited for indoors applications (i.e., [30,41,46,130]). Therefore, there is great opportunity for applying fingerprinting outdoors, i.e., in an open distributed collaboration of many users for building or refining a location system, such as the "OpenStreetMap" [135]. In addition, the ambient geomagnetism field can be used for distinguishing between indoors and outdoors environments, as well as creating a geomagnetic map for outdoors, by using the compass, in combination with the smart device's accelerometer and gyroscope.

Furthermore, BLE- and Bluetooth-based ad hoc networks that promote the collaboration of the different Bluetooth-equipped devices can be investigated in the future, as well as other packet parameters, apart from RSS measurements. For SLAM, a future direction can include the estimation of the starting point, which is currently a limitation. Wi-Fi is one of the most popular localization technologies today, with no additional software and hardware requirements. However, the Wi-Fi FTM (i.e., IEEE 802.11mc amendment) is still not widely available; therefore, alternative amendments could be evaluated with time-based ranging estimations. The RFID is another promising technology with high localization accuracy [118]; therefore, smart devices' applications with RFID readers can be developed in the future. Similarly, the UWB is recently deployed on smartphones [103], so it can be used for indoor navigation.

4.3.2. Real-Time World Testing and Deployment

Numerous technologies have only been evaluated in simulation environments so far; therefore, in the future, they should be tested in real-world conditions. For example, several VLC technology experiments in the discussed literature were only carried out in simulation environments (i.e., [44,108,112,113,115,128]). In the future, they should be tested in real environments under variable conditions, such as windows with ambient light, different wall colours, and reflective materials.

Furthermore, in [131], the experiments were carried out using a smartphone only in LoS conditions; therefore, challenges associated with multipath propagation were not sufficiently tested. In particular, different techniques for filtering out the noise and eliminating multipath effects for acoustic-based systems should be tested in real-world conditions in the future. Furthermore, throughout the literature, IMU-related tracking algorithms mostly assume a normal walking pace in implementing PDR, and no other paces from the real world are tested. In fact, the experiments are commonly carried out with only a single participant within a controlled environment; therefore, future directions for real-world testing can include multiple participants in large open crowded environments.

4.3.3. Cloud and Edge Computing

Most of the mobile positioning systems nowadays rely on cloud and edge computing services, and this is something that is expected to grow in the future.

Cloud computing includes the delivery of computing services over the Internet (Cloud) for achieving faster, flexible resource utilization and economies of scale. These resources include tools and applications, such as data storage, servers, databases, networking, software, analytics, and intelligence. In [136], a cloud-based computing system was proposed for Wi-Fi indoor positioning and navigation through a single-hop wireless network. The system consisted of a self-driving card, a core cloud, and a moving edge cloud composed of a small-box center (cloudlet) available in a wireless AP. The core cloud was responsible for storing all information in the corridors, including the wireless access point map and forwarding the destination positioning packet.The moving edge cloud, on the other hand, was used for calculating the route path, taking movement decisions, and making positioning estimations. Combined, the cloud network could provide the destination position and wireless access point map and effectively help navigate the cart towards its final destination.

Edge computing, on the other hand, is the range of networks and devices provided near the data source. In this way, the response time is improved, less bandwidth is required, and latency is reduced, which has a positive impact on the applications' performance and economic cost. Edge computing is useful for IoT and real-time applications with minimum latency, such as autonomous vehicles and multi-camera video analytics. In [137], a visible light positioning (VLP) system was developed, including a transmitter, a receiver, and an edge computing platform. The transmitter included LEDs, a microcontroller, and driving circuits, while the receiver was a smartphone that captured the LED images though its embedded front camera and used a series of imaging processing methods for obtaining the LED centroid coordinates. Both offline and online positioning were used for enhancing the flexibility and scalability of the system. It was concluded that, by placing more modules on the edge computing platform, both the CPU usage and the memory consumption of the smartphone decreased and the data traffic consumption of the smartphone increased. The memory consumption and CPU usage were found proportional to the data traffic consumption.

4.3.4. From Smart Sensors to 6G

Sixth generation wireless (6G), the successor to 5G cellular technology, is a promising technology for providing an arena of new service capabilities with positioning and sensing to be part of the wireless communications, in addition to the the incorporation of artificial intelligence (AI) and machine learning (ML). The AI and ML can improve the data processing, especially for system models that are difficult to design and solve. In addition, they provide feature extraction and motion modelling algorithms for tracking augmented reality (AR) and extended reality (XR) objects in the scene and estimating their location and orientation [134,138]. In particular, AR provides additional digital elements to the surroundings by utilizing the smart devices' camera and virtual reality (VR), which replaces the real environment with a simulated one, while XR provides the experience of being physically and spatially located in a virtual environment. The autonomous navigation and localization will be provided with augmented human and computer vision in NLoS imaging.

The evolutionary trend of 5G towards high frequency ranges, wider bandwidth, and massive antenna arrays deployment is intended to continue into the sub-Terahertz region (0.3–3 THz) in the 6G systems [139]. The sub-THz communications requires the deployment of extreme massive MIMO antennas [138]. The short wavelengths at THz can provide massive spatial multiplexing communications, accurate sensing, imaging, and spectroscopy [134]. The sensing applications include air quality monitoring, gesture recognition, explosives' detection, and gas sensing, as well as centimeter-level positioning [134].

The wireless devices equipped with 6G will gather information from different locations in an effort to create detailed 3D maps of the world, thus providing positioning, as well as mapping and sensing services. For instance, SLAM will not require prior knowledge of the environment [140]. Additionally, certain materials and gases that have vibrational absorption at particular frequencies throughout the THz band will be detected through the frequency scanning spectroscopy; so, the smart devices equipped with 6G will be capable of sensing certain chemicals and defects in the environment [134]. Furthermore, the provided µmWave frequencies [139] are expected to reach shorter distances with smaller beam widths, thus providing higher positioning accuracy.

The high-resolution sensing is also an integral part of the 6G systems. In addition, in the 5G new radio (NR) positioning, 6G carrier aggregation will be effectively used for combining the position reference signal (PRS) to a single signal and eliminating the various limitations associated with signal strength, time-based, and angle-based measurements (i.e., the signal strength accuracy depends on path loss—the time-based is limited by the bandwidth of the PRS aid and the angle-based accuracy is limited by the antenna array or aperture) [138]. In general, the 6G includes numerous promising features with the potential of merging imaging and communications for precise positioning.

5. Conclusions

Wireless positioning systems play an instrumental role in people's lives today and will continue to do so in the years to come. In this review, we provided a comprehensive taxonomy of the related research over the last 30 years, with respect to the localization technique and the wireless technology employed. First, with respect to the localization/positioning algorithms and techniques, the reviewed articles were classified according to the signal measurements employed (i.e., time-based, angle-based, and channel-based), the localization method (i.e., range-based, range-free, ML/AI), and the tracking method (i.e., DR, Filters, SLAM). Next, numerous wireless technologies were presented and discussed, with respect to localization, including satellite, cellular, RADAR, FM, LoRa, and SigFox, Wi-Fi, Bluetooth, UWB, geomagnetism, vision technology, VLC, RFID, acoustic, ultrasound, and infrared radiation. Finally, a statistical analysis of the results revealed gaps in the existing research and identified directions for future research.

In particular, although intensive research efforts have been made, significant challenges for designing future localization systems still remain, with respect to availability, cost, energy-efficiency, privacy issues, position accuracy, fault-tolerance, latency, and scalability. To date, none of the existing techniques can be considered as a one-solution-fits-all for the different indoors/outdoors environments, since the effectiveness of each method depends on the availability of the required data and technology, level of complexity, and the properties of the specific environment or the setup considered. Almost all considered approaches achieved only some of the performance criteria at the expense of others. Some technologies and techniques appear promising in simulations or controlled experiments, but without real-world testing to back up the claims made in the lab or during simulations. A promising future direction is hybrid positioning systems that can fuse different methods, measurements, and/or technologies for improving the existing localization systems. A good possibility in this direction, would be the implementation of intelligent handover systems, able to seamlessly transfer the localization responsibility from one wireless technology to another, with the overall aim of achieving continuous and transparent positioning for the end user in both indoor and outdoor environments.

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