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Systematic Review of Dynamic Multi-Object Identification and Localization: Techniques and Technologies

RASHID ALI[1,2], RAN LIU[1], YONGPING HE[1], ANAND NAYYAR[3,4], AND BASIT QURESHI[5], (Member, IEEE)

[1]School of Information Engineering, Southwest University of Science and Technology, Mianyang 621010, China
[2]Department of Computer Science, University of Turbat, Turbat Kech, Balochistan 92600, Pakistan
[3]Graduate School, Duy Tan University, Da Nang 550000, Vietnam
[4]Faculty of Information Technology, Duy Tan University, Da Nang 550000, Vietnam
[5]Department of Computer Science, Prince Sultan University, Riyadh 11586, Saudi Arabia

Corresponding authors: Rashid Ali (alirashid@mails.swust.edu.cn) and Anand Nayyar (anandnayyar@duytan.edu.vn)

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ABSTRACT Object identification and localization in indoor and outdoor environments are paramount issues in object–human interaction. Recent advancements in the data fusion capabilities of multi-sensor systems have paved the way for research on emerging object identification and positioning techniques. This review describes techniques and methods used in positioning technologies. State-of-the-art localization technologies are classified into range-based, range-free and AI-based categories. An in-depth analysis of localization approaches based on laser range finder, radio-frequency identification, ultra-wideband, inertial measurement unit, etc., are presented by providing a detailed comparison based on range, accuracy, measurement method, advantages, disadvantages, and their applications. Furthermore, we investigate state-of-the-art multimodal data fusion techniques that utilize probabilistic methods for the precise estimation of object identification in motion and its localization.

INDEX TERMS Indoor and outdoor positioning systems, identification and localization, unstructured environment, multi-sensor system, multi-object, positioning and localization techniques.

I. INTRODUCTION

In recent years, the potential of localization and identification has enabled objects (people, things) or robots to make judgments and perform useful work. Thus, the technological advancement of identification and localization in unstructured indoor and outdoor environments plays an important role. Several techniques, such as range-based, range-free, and AI-based, can be used for object identification and localization to perform tasks in a certain environment efficiently. If multiple objects exist in a particular environment, such sensors are essential for identifying and localizing multiple objects simultaneously [1], [2]. These sensors include radio-frequency identification (RFID), laser range finder (LRF), and ultrawideband (UWB) sensors. Automatic identification and localization methods are performed using RFID and LRF sensors to identify and localize the movements of objects. RFID, LRF, UWB, inertial measurement unit (IMU), Near-Field Communication (NFC), Bluetooth, ultrasound, and Wi-Fi are challenging to use localization and identification in indoor tracking tasks. Therefore, such technologies are applied to highly heterogeneous systems [3], [4].

An RFID system is considered the most widely used method, and it helps to identify and collect sensor data from objects located in an indoor environment. Similarly, LRF and visual sensors are used in an indoor environment, wherein RFID technology incorporates electromagnetic waves. Moreover, RFID technology communicates between the RFID reader and ID tags. RFID technology is robust to its lights condition and the influence of unknown objects. However, resolving the multiple object issue in a specified environment by utilizing RFID sensors is extremely difficult. The simultaneous object localization and identification (SOLID) [162] in their respective locations involve the use of multiple sensors (e.g., RFID and LRF). In simultaneous localization and mapping (SLAM), LRF and vision sensors have been used

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extensively for mobile robots [5]. However, multiple sensors must be equipped and configured on a specific robot to provide maximum coverage in a certain environment and accurate information about a particular object's identification and localization.

After reviewing the literature, such methods have been suggested to perform identification and localization by using a combination of RFID and LRF sensors. The Bayesian approach was used to reduce estimation errors in [6]. Mobile robots are widely known for fulfilling such criteria because most robot technologies are equipped with sensors, such as IMU, LRF, UWB. A variety of object recognition technologies have been suggested on the basis of visual processing [7], [8]. The researchers in [9] addressed the issue of identifying and detecting household objects by utilizing visual cameras. However, data obtained via sensors can be noisy in a dynamic environment with multiple objects, and thus, may provide incorrect identification and localization [10]. In [11], the probabilistic approach was applied to compensate for estimation errors using a particle filter. Data obtained from multiple sensors, such as LRF and UWB, are always incorporated into such dynamic environments to obtain good identification and localization accuracy.

RFID systems (including passive and active RFID) have become familiar nowadays. In [12], passive tags, such as parallelogram and triangular tags, were reduced on the basis of different allocation patterns. Passive RFID sensors are less expensive than active sensors [13]. High frequency (HF) band RFID has been used to improvise precision [14]. Although RFID is useful in identifying objects, it cannot achieve each application's goal that requires human identification. In [15], the received signal strength (RSS) information was characterized on the basis of a probabilistic sensor model that was also suggested for navigating a mobile agent and localizing RFID tags. The technology involves objects, such as humans wearing RFID tags, and transforms the activities connected to all those tags [16]. In [17], [18], several RFID-based localization schemes were suggested. The authors focused on object localization and frequently included sensor nodes, such as reference tags to improve localization.

Similarly, RFID systems have been researched to resolve the issues of localization. However, adequate precision may not be achieved during localization. Consequently, laser-based localization has been incorporated into recognition that uses RFID systems in the literature review [19]. The major contributions of this review are as follows.

- We present different localization and identification techniques, including a classification of methods with emerging positioning technologies and recent key challenges to object identification and localization.
- We summarize indoor and outdoor localization and identification approaches based on LRF, RFID, and other sensors with in-depth analysis.
- Overall, we present a review of different state-of-the-art sensor technologies and their multimodal data fusion techniques, i.e., probabilistic methods that precisely estimate moving object localization and identification.

The subsequent sections of this paper are organized as follows. Section II presents state-of-the-art localization and identification techniques and their classification. Section III describes the indoor and outdoor positioning technologies. Section IV focuses on localization and identification by using probabilistic methods. Section V concludes the paper and provides suggestions for future research.

II. CLASSIFICATION OF LOCALIZATION AND IDENTIFICATION TECHNIQUES

At present, many techniques are available for determining the position between sensor nodes. For example, the global positioning system (GPS) is extremely useful for an outdoor environment; however, it is not useful for an indoor environment because buildings/obstacles block radio signals [20], [21].

Localization and identification methods for wireless sensor networks (WSNs) are divided into three groups. The first group includes range-based, range-free and AI-based methods. Range-based methods, such as time of arrival (ToA), which physically calculates distance through the speed and propagation time of a signal. Meanwhile, the angle of arrival (AoA) technique estimates the location position of the node of interest (NOI) by obtaining the direction of the signal sent by attached nodes through an array of antennas and multiple receivers. Simultaneously, the RSS Indicator (RSSI) measures the power received by the receiving node, calculates propagation losses, and then transforms them remotely by using a theoretical or empirical model of signal path losses [22].

The second group comprises location techniques, which are further classified into four groups: techniques based on distance estimation, multidimensional scaling (MDS) [23], and position estimation (range-based), multi-hop scenario (range-free) and ANN, ANFIS, PSO, fuzzy logic, etc., (AI-based) techniques. Range-based techniques are required to calculate the distance between a group of nodes to estimate the NOI position. This group includes multidimensional scaling (MDS) [23], ad-hoc positioning systems (APS) [24], and circular and hyperbolic positioning algorithms [25]. Meanwhile, range-free techniques estimate the position of the NOI by using RSS, and thus, they are not required to estimate the distance between nodes. This group includes distance vector-hop (DV-Hop) [20], approximate point in a triangle (APIT) [20], [26], centroid [20], rectangular intersection, circular intersection, and hexagonal intersection [27]. Position estimation techniques are based on the intersection of multiple communication ranges to locate the NOI; the techniques are triangulation, trilateration, multilateration, etc., as shown in Fig. 1.

A. RANGE-BASED LOCALIZATION TECHNIQUES

Improving the understanding of localization is necessary to consider other existing technologies. These techniques

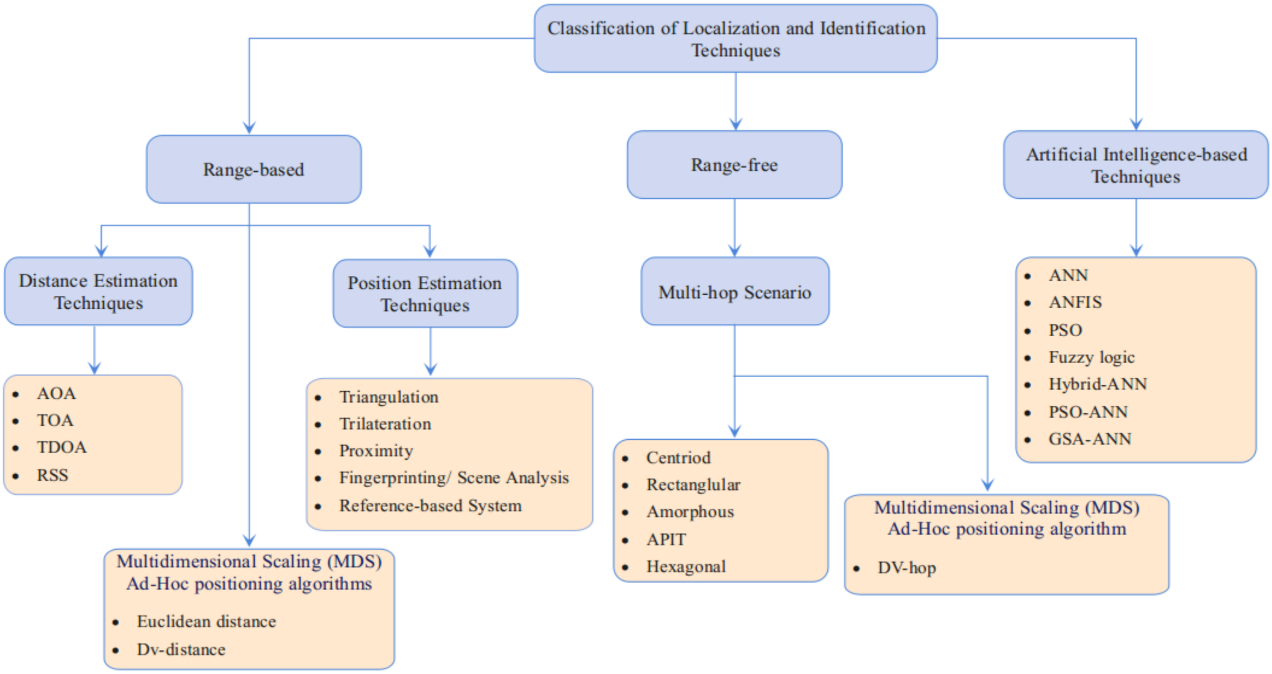

FIGURE 1. Classification scheme for localization techniques.

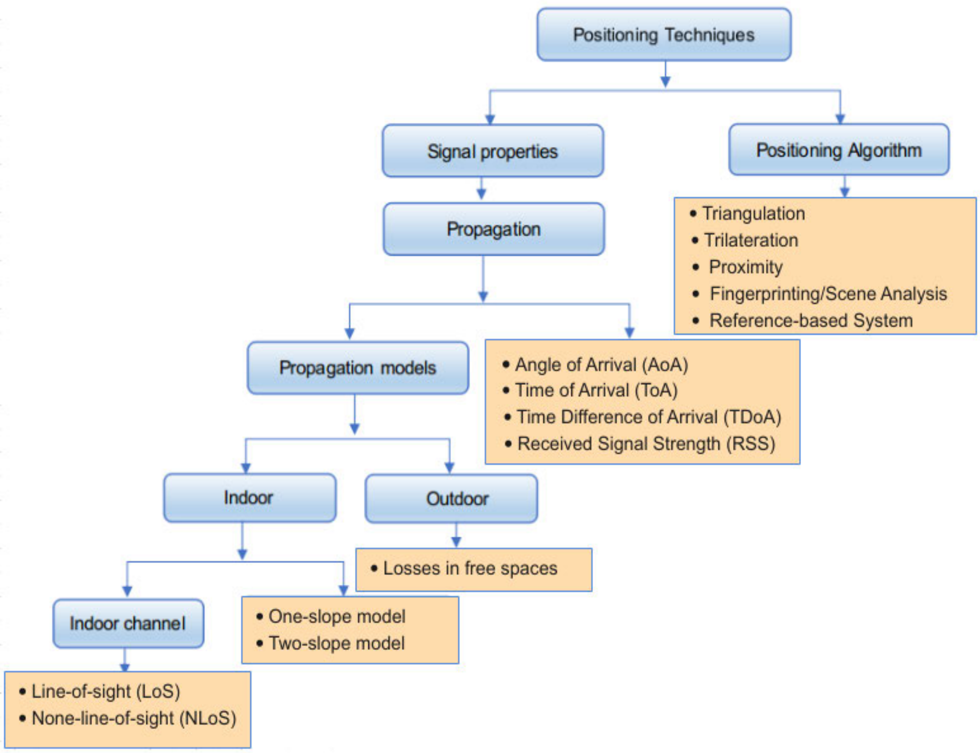

FIGURE 2. Positioning techniques.

in accordance with can be classified by their measurement principle or the technology they use. In measurement principle classification, current technologies are differentiated by their methods for locating and determining an object's (e.g., a human) position. The techniques are categorized as shown in Fig. 2.

1) SIGNAL PROPERTIES

Propagation: A set of physical phenomena lead the waves from the transmitter to the receiver; when a radio wave hits an obstacle, a part of the wave is reflected, and the wave experiences a certain loss of intensity. Such a phenomenon, called reflection, makes the incident wave angle equal to the reflected wave angle. A radio wave can propagate in several directions. After being reflected several times, a source signal can reach a station or access point after taking many different routes, called a multipath. As the antennas' direction increases, the main path exhibits more intensity than the rest of the paths, and its losses will be similar to those produced in free space, while the losses of the other paths will deviate more or less from them [92].

- *AoA*: This method is defined as the angle obtained between the propagation direction of a wave against a reference for which the orientation is known. The reference is a direction against which we measure the AoA. This reference is expressed in degrees in a clockwise direction. The most common method for obtaining AoA measurement is to use an array of directional antennas [28], [29], as shown in Fig. 3. This method uses at least two known reference points (A, B) and angles θ_1 and θ_2 to identify the 2D location of the target P. AoA estimation, commonly referred to as direction finding, can be achieved using directional antennas.

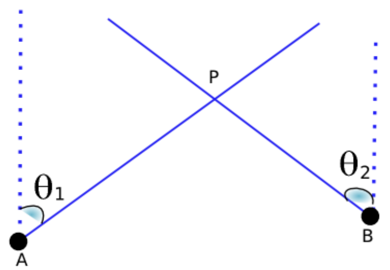

FIGURE 3. Positioning technique on AoA measurement.

- *ToA*: Measuring the ToA signal is a robust method for estimating distances used among other signals in GPS. This technique measures the time as a signal travels from one node to another at a known speed. For example, sound waves travel at a speed of approximately 344 m/s with a temperature of 21°C. Thus, an ultrasound pulse is sent by a node, and it reaches another node after 14.5 ms, and thus, conclude that the distance between them is 5 m. As illustrated in Fig. 4 [30], ToA measurements can be performed for signals from at least three reference points to allow 2D positioning. This type of technique requires a clock with high accuracy in the communication system. The best-known system for this technology is GPS [31].

  This technique has two important advantages: extremely few nodes are required to estimate user position, and no synchronization is necessary between systems. The major disadvantages of this method are as follows: expensive hardware (sometimes large) is necessary, and the accuracy of measurement is reduced as the mobile terminal moves away from the node. Precision is affected by the multipath effects and the obstacles present in the area. The mobile terminal, located at (x_0, y_0), is assumed to transmit a signal at time t_0. The N base stations located at $(x_1, y_1), (x_2, y_2) \ldots, (x_N, y_N)$ receive the signal at time $t_1, t_2 \ldots, t_N$. As a measure of performance, the cost function can be calculated using (1) [165].

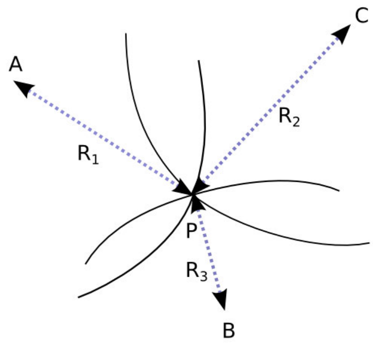

FIGURE 4. Positioning technique on ToA measurement.

$$F(x) = \sum_{i-1}^{N} \alpha_i^2 f_i^2(x), \tag{1}$$

where α_i can be selected to reflect the reliability of the received signal i, and $f_i(x)$ is given as (2).

$$f_i(x) = \{c(t_i - t) - \sqrt{(x_i - x)^2 + (y_i - y)^2}\}, \tag{2}$$

where c is the speed of light, and $x = (x, y, t)^T$, this function is formed for each unit of measure, $i = 1, \ldots, N$ and $f_i(x)$; can be set to zero with the appropriate choice of x, y, and t. Then, the estimated location is determined by minimizing the function $F(x)$.

- *Time Difference of Arrival (TDoA)*: Synchronization is required between the sender and the receiver. Systems, such as Calamari [32], Cricket [33], and an ad-hoc localization system (AHLoS) [34], use a technique called TDoA that allows a more complex time synchronization. In these systems, as shown in Fig. 5, the transmitter emits an acoustic pulse (ultrasound) and a radio pulse, and the receiver compares the arrival time of both pulses. To determine each signal's flight speed, the time difference between arrivals indicates the distance between the sender and the receiver. For each measurement in TDOA, the transmitter must be in a hyperbola with a constant difference range between two units of measurement. The equation of the hyperbola is given by (3).

$$R_{i,j} = \sqrt{\{(x_i - x)^2 + (y_i - y)^2 + (z_i - z)^2\}} \\ -\sqrt{\{(x_j - x)^2 + (y_j - y)^2 + (z_j - z)^2\}}, \tag{3}$$

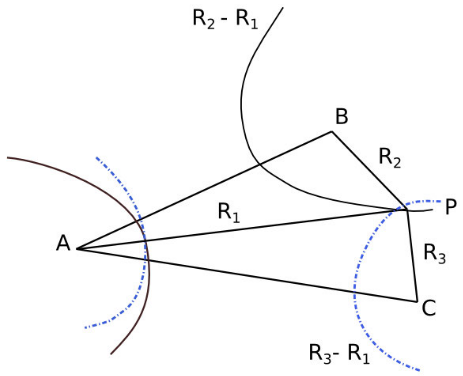

FIGURE 5. Positioning technique on TDoA measurements.

where (x_i, y_i, z_i) and (x_j, y_j, z_j) represent the fixed receptors i and j, and (x, y, z) represent the coordinates of the target [164].

The different measures tend to produce a mean error of 74% in the estimate. More accurate measurements can be achieved by post-processing the data using noise cancellation techniques, digital filtering, and peak detection and calibration. Some authors report a mean error of 10% in the estimation, while others claim to obtain an error of approximately 1% at distances less than 9m [35]. Such systems offer minimal errors in estimation, which have two limitations that significantly reduce their applicability in the real world.

1) Limited Coverage: Such systems can cover between 3m and 15m [36], which is only a fraction of the communication range of radio-frequency transmitters.

2) Hardware cost: Such systems require a separate transmitter/receiver pair, implying greater size, cost, and energy consumption.

- *RSS*: RSS generally requires RSSI measurement, a parameter that is typically delivered by a piece of equipment. To estimate an object's location by using fingerprint approximation at different points, so the system initially requires measuring signal intensity as established previously. A pattern is drawn and compared with a database that allows translating the pattern information into a position. The drawback of this method is the waste of considerable time performing a sample data collection to reduce probability errors. To find a location by using references, LS_1, LS_2, and LS_3 represent path loss, and the system has emitters placed in the area to be located, as shown in Fig. 6. A correlation can be made to determine the location by continually comparing the object RSSI to be located and the fixed emitters. However, more equipment must be incorporated into the system to perform this task [37]. The authors in [38] suggested an algorithm for localization that uses the mobile anchor node. Moreover, higher RSSI positions were reported as beacon points in their algorithm, where a sensor node has minimum error while obtaining a transmission from

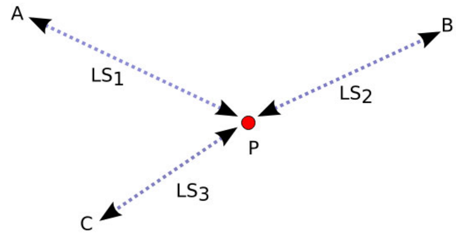

FIGURE 6. Positioning technique on RSS measurements.

mobile anchor nodes. Suppose that for the transmitted signal $s(t)$, the received signal in the unit of measure i is x_i. Suppose $x_i(t)$ is corrupted by noise $n_i(t)$ and a delay of d_i, then $x_i(t) = s(t - d_i) + n_i(t)$. Similarly, the signal $x_j(t) = s(t - d_j) + n_j(t)$, arriving at the unit of measure j has a delay of d_j and is corrupted by noise $n_j(t)$. The cross-correlation function of these signals is determined by integrating the phase product of two signals received at time T. The TDoA estimate τ is the value that maximizes $R_{xi,xj}(\tau)$, e.g., range differences. This approach requires the units of measure to share a precise time reference signal but does not impose any mobile destination requirements. Processing techniques in the frequency domain are generally used to calculate τ (4).

$$\hat{R}_{xi,xj}(\tau) = \left\{ \frac{1}{T} \int_0^T x_i(t) x_j(t - \tau) dt \right\}, \tag{4}$$

A measurement-based TDoA method for the delay was proposed in [163] by using 802.11 WLAN, eliminating initial synchronization.

a: PROPAGATION MODELS

A propagation model is an empirical mathematical formulation designed to characterize the propagation of radio waves within a given environment, as shown in Fig. 7. Propagation models predict the loss of a path between a base station and a receiver [93]. Predictive models can generally be classified into empirical, theoretical, or a combination of the two, i.e., semi-empirical. Empirical models are based on measurements, and theoretical models are based on the fundamental principles of radio wave propagation. Expressions, diagrams, and algorithms represent a given environment's radio characteristics [94].

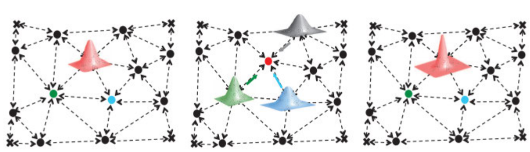

FIGURE 7. Belief propagation steps (an illustrative example).

The models predict the path loss that an RF signal may experience between a base station and mobile or fixed receiver. The advantage of modeling radio channels [95], considering the characteristics of a path between a transmitter (Tx) and a receiver (Rx), in determining the viability of a project to be planned in certain sectors. Thus, an estimate can be made regarding the required equipment's needs, costs, and capacity.

An empirical model can be used, and it will be compared with a convenient theoretical model. In general, the characterization of a radio link can be expressed as shown in (5).

$$P_{Rx} = P_{Tx} + G_{Tx} + G_{Tx} - L_p - L_{others}, \tag{5}$$

where P_{Rx} is the power received by the receiver, P_{Tx} is the power transmitted by the transmitter, G_{Tx} is the gain of the transmitting antenna, G_{Rx} is the gain of the receiving antenna, L_p is the power loss of the signal due to propagation, and L_{others} is loss due to another reason.

The most widely used model is the log-normal shadowing model [96], a generalization of the Friis free space equation because theoretical and experimental studies support this model in indoor and outdoor settings. The model can be expressed by (6).

$$L_p[dB] = L_0 + 10.n.\log_{10}(\frac{d}{d_0}) + X_g, \tag{6}$$

Log-Normal Model Parameters Estimation via Maximum Likelihood: Parameters η and σ_x^2 are typically unknown and can be measured in channel measurements. A collection of N average power observations is obtained from different transmitter distances and various position points in the region of interest such that N pairs of $P_{Rx}(d_i)$, d_i measurements are accessible. Powers are proposed to be provided in dB due to its simplicity. As shown in (7), the log-likelihood parameter is determined from N observations' joint probability density function.

$$L(n, \sigma_x^2) = -N\ln(\sqrt{2\pi\sigma_x^2}) - \frac{1}{2\sigma_x^2}\sum_{i=1}^{N}[P_{Rx}(d_i) - P_{Rx}(d_0) - 10\eta\log(\frac{d_i}{d_0})]^2, \tag{7}$$

When the previous expression is minimized with respect to η, the estimate is given by (8).

$$\hat{\eta} = \frac{\sum_{i=1}^{N}\log(\frac{d}{d_0})[P_{Rx}(d_i) - P_{Rx}(d_0)]}{10\sum_{i=1}^{N}(\log(\frac{d}{d_0}))^2} \tag{8}$$

By substituting η for $\hat{\eta}$ in the equation and differentiating with respect to σ_x^2, (9) is obtained.

$$\sigma_x^2 = \frac{1}{N}\sum_{i=1}^{N}[P_{Rx}(d_i) - P_{Rx}(d_0) - 10\hat{\eta}\log(\frac{d_i}{d_0})]^2, \tag{9}$$

Estimator for Log-Normal Distance: Once the channel parameters are estimated, power measurements can approximate the distance between a transmitter and a receiver. By substituting the values of $\hat{\eta}$ and σ_x^2 and redefining the equation for a simple P_{Rx} power observation, (10) is obtained.

$$L(\hat{\eta}, \hat{\sigma}_x^2, d) = -\ln(\sqrt{2\pi\hat{\sigma}_x^2}) - \frac{1}{2\hat{\sigma}_x^2}[P_{Rx}(d) - P_{Rx}(d_0) - 10\hat{\eta}\log(\frac{d}{d_0})]^2, \tag{10}$$

By deriving the expression with respect to d, the (11) of the distance estimator is obtained.

$$\hat{d} = d_0 10^\wedge[\frac{P_{Rx}(d_0) - P_{Rx}}{10\hat{\eta}}], \tag{11}$$

1) *Indoor Propagation Models:* Indoor radio propagation is dominated by the same mechanisms as those in outdoor radio propagation, such as reflection, diffraction, refraction, and scattering. However, conditions vary considerably more depending on different physical factors involved in building design, height, and the materials used to build them [97]. In general, indoor propagation channels can be classified into two categories.
1. Line of Sight (LoS): A direct vision exists between a transmitter and a receiver.
2. Non Line of Sight (NLoS): No direct vision exists between a transmitter and a receiver due to different obstacles, such as walls, furniture, windows, people, floor, and ceiling. Multiple studies have yielded different methods for predicting radio wave propagation in an indoor environment. The two most widely used propagation models are described as follows.
   - *One-Slope Model*: The simplest propagation model exhibits logarithmic dependence between propagation loss and distance; it is extremely easy to use and implement, and losses are given by [98]. As indicated in (6), where L_0 is the loss at the reference distance, d_0, $L_0 = 20\log(4\pi d/\lambda)$($\lambda$ is the wavelength in meters). n is the propagation index, d is the distance between the sender and the receiver, and X_g is a normal (or Gaussian) random variable with zero means.
   - *Two-Slope Model*: A propagation model that is similar to the one-slope model, with the only exception being the path for which propagation losses are to be calculated, is divided into two as shown in (12). The first is up to a distance d_r, and the second is after it is given.

$$L_p[dB] = \begin{cases} L_0 + 10.n_1.\log_{10}(\frac{d}{d_0}) + X_{g1} d \le d_r \\ L_1 + 10.n_2.\log_{10}(\frac{d}{d_r}) + X_{g2} d > d_r \end{cases} \tag{12}$$

   L_0 and L_1 are the losses at reference distances d_0 and d_1, respectively; n_1 and n_2 are the propagation indices; d is the distance between the transmitter and the receiver; and X_{g1} and X_{g2} are normal or Gaussian random variables with zero mean [95].

2) *Outdoor Propagation Models*
Existing losses are caused by free space in outdoor environments if they are considered unobstructed. These losses are defined as the quotient of the power radiated by transmitting antenna and captured by receiving antenna [99], (13).

$$L_p[dB] = 10.\log_{10}(\frac{4\pi d}{\lambda}), \tag{13}$$

By using practical units in dB, it can be expressed as seen in (14).

$$L_p[dB] = 32.45 + 20\log_{10}(f[MHz]) + 20\log_{10}(d[km]), \tag{14}$$

The fact that the losses of the antenna due to its type, characteristics, and gain are independent is extremely important to its electromagnetic waves when their propagation is attenuated under the distance's inverse law.

2) POSITIONING ALGORITHM

a: TRIANGULATION

Triangulation performs location-based estimation on RSSI. The distance at which a TAG is located is determined. If the TAG is placed in the distance, then its signal intensity can be reduced and stored in a precise database, translating the measured RSSI into a distance. Subsequently, an algorithm that statistically reduces the error and improves precision is applied [39]. Moreover, triangulation is performed instead of using distances to determine the distance at which a TAG is located. An interval where the TAG is highly likely to be found is identified. Triangulating a point in space is not realized, but a probability region is obtained where the TAG can be found. The diagram typically appears as shown in Fig. 8(a), where each reader has a probability zone where the TAG can be located and an area where these zones intersect. This technique requires a larger number of readers to improve accuracy [40].

In this method, the mobile node's location is based on the receiver's capability to identify the reception angles of location signals and the knowledge of position emitters. The major drawback of this method is precisely calculating the angle with which the emitter is sending its signal because extremely precise directional antenna systems are required. Fig. 8(b) illustrates the position calculation principle used by the triangulation method. The positions of nodes A and B are known. The objective is to find the position of node C. Receivers A and B can detect the angle at which the signal reaches them; i.e., it reaches node A with an angle α and reaches node B with an angle β. When finding distance d, node C is positioned locally. This distance is determined using the following trigonometric expression (15).

$$d = \frac{l}{1/\tan\alpha + 1/\tan\beta}, \tag{15}$$

where l is the known length between nodes A and B.

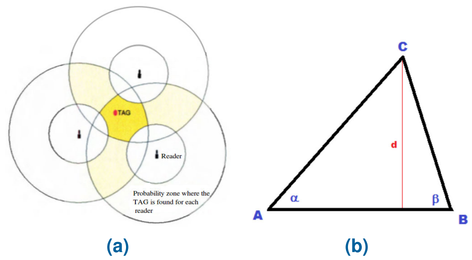

FIGURE 8. (a) and (b) are the illustrative examples of triangulation measurements.

b: TRILATERATION

Trilateration is another location algorithm used for indoor environments, which is highly similar with regard to its acquisitive nature to the method used by GPS. In both cases, experimental data acquisition is realized by measuring the distances between reference points. The only difference between the two is that in trilateration, the reference points are fixed as an illustrative example shown in Fig. 9, while they orbit around the Earth in GPS [41], [42]. The literature review in [43] provides location-based services, including navigation and tourism, where GPS is the most extensively used satellite positioning system. Given a variety of obstacles, GPS is not ideal for providing fairly accurate tracking in an indoor environment due to the issue of NLOS. Several technologies were presented in [44], [45] for solving indoor localization problems. In [46], [47], ToA, the gap between the transmitter and the receiver was estimated using the signal's travel time and speed.

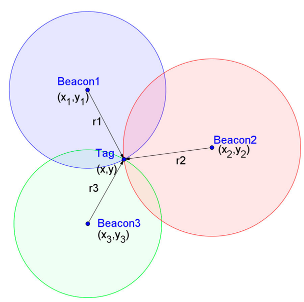

FIGURE 9. Illustrative example of trilateration algorithm measurements.

c: PROXIMITY

The proximity technique determines whether an object is close to a known position. The object's presence can be approximated with limited coverage by using a physical phenomenon [48], [49]. Three general methods are used for determining the proximity between points.

1. *Physical Contact Detection*: is the most basic method of proximity. Pressure sensors, touch sensors, and capacitance detectors are frequently used.

2. *Monitoring Wireless Cellular Access Points*: In this method, a mobile device can be monitored to determine if such a system exists within the range of one or more access

points in a wireless cellular network. It is another implementation of the proximity location technique. An array of antennas is spread, each with a well-defined position. When a single antenna detects the mobile device is considered to be in the same location when more than one antenna is detected and considered at the antenna's location that receives the strongest signal.

3. Observing Automatic Identification Systems: Examples of such systems are computer log-in histories, credit card point-of-sale terminals, and telephone call records.

d: FINGERPRINTING/SCENE ANALYSIS

The fingerprinting/scene analysis technique for RSSI-based localization uses a zone calibration based on the principle that when characterizing a point in space. The zones near this point exhibit similar characteristics; whatever is performed to select many points to calibrate, and a sample is generally maintained for more than $1h$ at each point to obtain sufficient samples from all points of view. When a TAG is detected, a certain number of samples are created. These samples are made to pass through an algorithm, and a conclusion is drawn with regard to the type of behavior they exhibit such that they can be associated with any of the previously characterized positions. A scene can be a visual image (obtained using a camera) or any other physical parameters that can be measured, such as the electromagnetic characteristics that are exhibited when an object is in a certain position and orientation. A probabilistic approach with RSS observation was used for indoor positioning [50]. Bayesian methods were used across a large number of data samples to improve the accuracy of a fingerprinting database [51], [52]. Scene analysis techniques based on the recognition of patterns are also used, such as the k-nearest neighbor (k-NN) method, learning paradigms, and automatic processing of artificial neural networks (ANNs), smallest M-vertex polygon (SMP), and support vector machines (SVMs) are discussed in AI-based techniques section.

e: REFERENCE-BASED

The reference-based technique is the most popular reference method in which reference TAGs are used (TAGs must be equal to the TAGs to be tracked). The most similar possible characteristics when comparing the RSSI, few variables, such as the battery life or the difference between the quality of supposedly identical components, comprised each TAG's internal circuitry [53]. A technique was suggested in [54] for the tracking of RFID-tagged baggage through the modification of RSS and the reading of RSS rates without reference tags. Many optimization techniques were proposed in [55] for the enhancement of RSSI-based localization accuracy. Such systems operate by comparing any other TAG to be located with the reference TAG and readers, obtaining a relationship among all the RSSIs, and determining which reference TAGs are used. To find the closest fixed TAGs to the mobile TAG by merely seeing which RSSI values are closest. To obtain the TAG position, the coordinates of the TAGs closest to the mobile TAG are used to its weight, and the most probable location is determined with the least error. Such a model identifies the reference TAG closest to the TAG to be detected, locating the second closest TAG consecutively until the desired number of closest neighbours is obtained [31], [56]. Each reference TAG is assigned a percentage of the total value of the mobile TAG coordinates to provide its coordinates in a weighted manner and then adds the coordinates of these close neighbors. Thus, 100% of the mobile TAG coordinates are formed by a weighted average of the TAG coordinates closest to it. Fig. 10 shows a mobile TAG and illustrates its four closest neighbors and how the mobile TAG position can be obtained by averaging the positions of its neighbors.

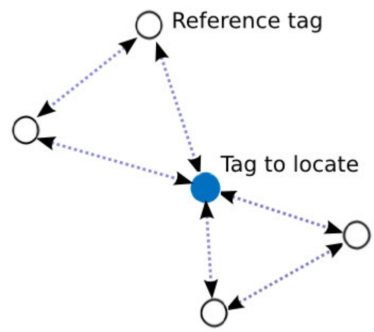

FIGURE 10. Mobile TAG within the closest fixed TAGs.

3) RANGE-BASED TECHNIQUES IN TERMS OF MDS AD-HOC POSITIONING ALGORITHMS

1) *Euclidean Distance:*
The Euclidean distance is a positive number that indicates the distance in a straight line or the shortest possible path between two points in space where the axioms and theorems of Euclid's geometry are fulfilled. To find the smallest sum of the weighted Euclidean distances of n fixed points with coordinates (a_i, b_i) being the final location point in space with coordinates (x, y), as shown in Fig. 11, Euclidean spaces that perceive for object/human localization can be 1D, 2D, or 3D [175]. The mathematical model can be seen in (16).

$$min_{x,y} = \{W(x, y) = \sum_{i=1}^{n} w_i d_i(x, y)\},$$

where,

$$d_i(x, y) = \sqrt{\{(x - a_i)^2 + (y - b_i)^2\}}. \tag{16}$$

The problem is analyzed from the nonlinear perspective under the condition that considers $d_i(x, y)$.

2) *Distance Vector (Dv-Distance)*:
The Dv-distance method [174] distributes each node that receives information from one or more neighbors directly connected to it. The iterative process continues until no information is exchanged between neighbors.

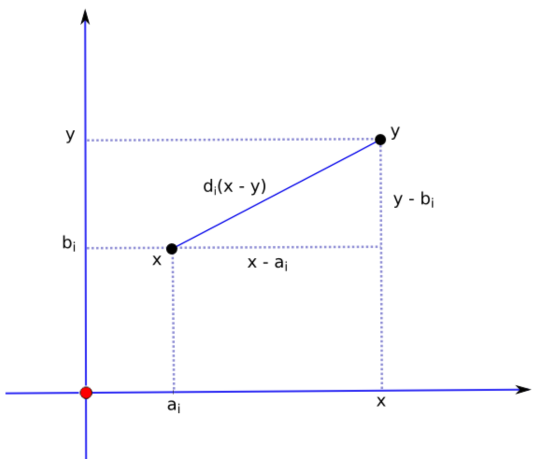

FIGURE 11. Euclidean distance between two points x and y.

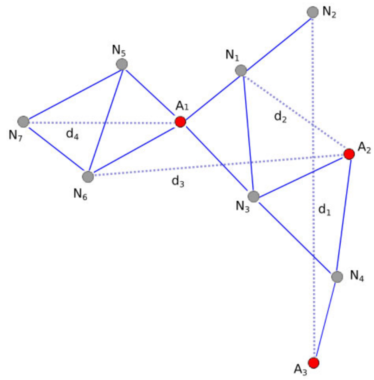

FIGURE 12. Illustrative example of the Dv-distance technique.

The asynchronous process does not require all nodes to run simultaneously.

For example, Fig. 12 shows the Dv-distance with the red node as anchors (A_1, A_2, A_3), and the gray circles represent the unknown node denoted by $(N_1, \ldots, N_7)$. The solid blue line indicates that the nodes directly communicate. The dashed blue line indicates the Euclidean distance between the anchor and unknown nodes, i.e., the distance between two points node represented as $dist(A_x, A_y)$. RSSI can be used to compute the distance in both neighboring nodes. The accumulated path distance between non-adjacent nodes can be used to calculate the distance between them. d_1 represents the distance if the path is expressed as $(A_3, N_4, N_3, N_1, N_2)$; hence, distance is mathematically represented by (17).

$$d_i = \{dist(A_3, N_4) + dist(N_4, N_3) + dist(N_3, N_1) + dist(N_1, N_2)\}. \tag{17}$$

4) DISTRIBUTED RANGE-BASED TECHNIQUES WITH ONE OR MORE NODES

1) *Monte Carlo Localization (MCL) for Mobile Sensor Networks:*
The authors of [69] presented a technique that consists of an adaptation of the MCL method, which was developed for use in mobile robot localization. Such an adaptation aims to make the MCL system usable in applications with mobile sensor networks. MCL is a particular filter that combines probabilistic models of robot movement and perception. In the indoor navigation process, dead reckoning, which consists of the current position (known as the initial position) and the speed applied over the elapsed time, is used [70]. MCL's core principle is to use a set of weighted samples to specify the posterior distribution of possible locations. Thus, every process can be divided into the phases of prediction and updating. The robot performs a movement during the prediction phase and increases the uncertainty of its position. New measurements are integrated into the updating phase, such as observations of new beacons to filter and update the information. The process repeats itself, and the robot updates its predicted location continuously.
In the case of a sensor network, MCL for WSNs assumes that nodes are non-uniformly dispersed and that no control is implemented over the mobile beacons' movement. The algorithm begins with an initialization phase, during which an assumption is made that no node knows its position, and a set of samples is initialized randomly among all feasible locations. The set of locations is updated at each step on the basis of possible moves and new observations. A node's location is estimated by calculating the mean location of all regions in the sample set. Therefore, a prediction phase and a filtering phase occur for each set of samples. A node undergoes transition distribution during the prediction phase to estimate its feasible locations on the basis of prior samples and their movement. The node then uses the new information received during the filtering phase to minimize predicted locations that are inconsistent with the observations. Resampling is performed to retain the number of samples from the location. The MCL method in [71] can provide a specific position, although it suffers from severe memory limits, low mobile beacon density, and highly irregular transmissions in the network.
2) *Localization System Using Mobile Robots:*
A localization technique for delay-tolerant sensor networks (DTSN) was introduced in [72]. A DTSN is applied to track a location for a long time and is described by the absence of interactive data traffic between sensors. Sensors are spread randomly and organized into one or more clusters that can be disconnected from the others [142]. Every cluster has a cluster leader wherein the information from the remaining cluster's sensors is grouped. A set of mobile and wireless robots, i.e., robomotes [73] or unmanned aerial

vehicles, can roam the network to collect data from cluster leaders or reconfigure sensors dynamically.
This technique utilizes mobility to minimize location errors and the number of static beacons. In addition, the authors developed a state estimation algorithm based on a robust extended Kalman filter (REKF) for locating a node in DTN. on the basis of the strength of signal measurements received in a mobile robot, and location is solved using an online estimation technique in a dynamic and nonlinear system.

3) *Online Distributed Localization by Using a Moving Target:*
In [74], [75], the authors proposed a distributed and online scheme that is capable of simultaneously locating nodes while tracking a moving target. A set of reference nodes equipped with GPS receivers and acting as beacons is found within the network. In the proposed algorithm, the sensors use observations of a moving target to improve the estimates of the positions of the target and the sensors. The sensors begin with an estimate of their position provided by the connectivity between them and the beacons. They then perform moving target detection to update their positions. Given that the range of action (S) is normally less than the range of communication (R), the target's narrow restrictions help locate nodes more precisely. The initial estimate of each node is provided by the centroid of the intersection of the bounding boxes of the reference nodes with connectivity.
Two situations are considered in this system. The first situation assumes that the target knows its position at all times. That is, it behaves similar to a mobile beacon. When the aforementioned beacon begins to move, it broadcasts its coordinates to the nodes within its connectivity radius. Every time a node receives a beacon message, it updates its position by launching a new constraint that consists by making the previous limiting box's intersection with the limiting box of the beacon. That is, a box with a side equal to 2S and whose centroid is the beacon's position, where S is the radius of action of each node (assuming they all have the same).
The second situation assumes that the moving target does not know its coordinates beforehand. The target's position is estimated as the intersection of its initial limiting box (the entire area in which the network is deployed) with the limiting boxes, by increasing its radius of action, with the nodes of its connectivity. In this manner, the positions of the sensors and the moving target are updated. Thus, K is the set of nodes within the radius of action of the moving target, and its limiting box Q_T is defined by (18).

$$Q_T \rightarrow Q_T \bigcap_{k \in K} (x^k_{min} - S, x^k_{max} + S) \times (y^k_{min} - S, y^k_{max} + S), \quad (18)$$

where x^k_{min}, x^k_{max}, y^k_{min} and y^k_{max} are the bounding box coordinates for the position of the k-th node, to improve the position estimates of the remaining network nodes, the authors consider two situations. The first situation involves updating the corners of the limiting box Q_T of a mobile node, as shown in (18). The second situation takes the centroid of the said bounding box, increasing the mobile node's position uncertainty, as shown in (19). The two equations are presented below, where Q_i is the bounding box of the node to update.

$$Q_i \rightarrow \cap_i (x^T_{min} - S, x^T_{max} + S) \times (y^T_{min} - S, y^T_{max} + S), \quad (19)$$

$$Q_i \rightarrow \cap_i (x^T_{est} - S, x^T_{est} + S) \times (y^T_{est} - S, y^T_{est} + S), \quad (20)$$

where x^T_{est} and y^T_{est} are the estimated positions of the moving target at the bounding box's centroid. Despite the loss of information propagated with the centroid (20), the total error in network location is significantly reduced.

4) *Localization With Mobile Beacons:*
The technique proposed in [76] uses one of the basic rules in geometry: a bisector perpendicular to a chord–a line that joins two points–passes through the center of the circumference in which the two points meet, as shown in Fig. 13(a). Considering that the transmission radius of a sensor is a 2D circumference and the center of the circumference indicates sensor position, node position can be easily calculated on the basis of the aforementioned rule if two strings can be obtained [156].

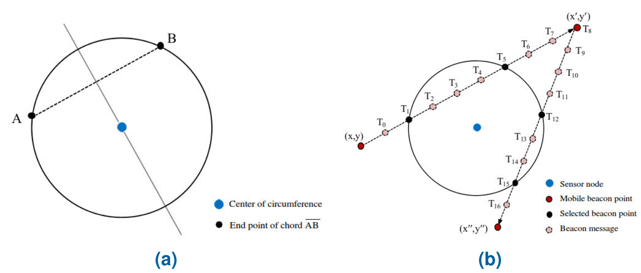

FIGURE 13. (a) The bisector perpendicular to a chord passes through the center of the circumference where the two points of the chord meet. (b) Selection of beacon points. The beacon moves from x, y to x'', y'' through x', y', sending beacon messages with a constant interval.

This mechanism uses mobile beacons that move around the area where the network is deployed and periodically emit messages that contain their current locations. Once the sensors receive the beacon messages, the valid points and chords are determined in Fig. 13(b), and then the position of each node is estimated as the center of the circumference, as shown in Fig. 14.

B. RANGE-FREE LOCALIZATION TECHNIQUES

Range-free localization techniques do not need to estimate the distances between nodes. The advantage of such

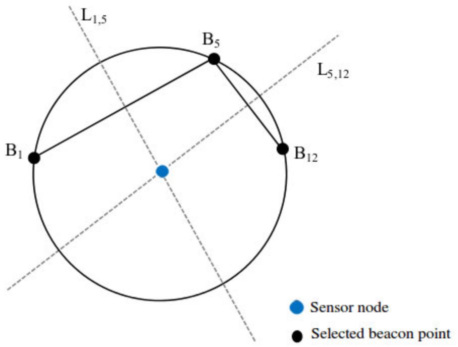

FIGURE 14. Estimation of position. Two strings are generated from three points selected in the previous phase B_1, B_5, and B_{12}. Considering that lines $L_{1,5}$ and $L_{5,12}$ are the corresponding perpendicular bisectors to the chords B_1, B_5, and B_5, B_{12}, calculating the equations of these bisectors is easy to determine the position of a sensor.

techniques is that sensors do not require additional hardware to measure their distances. The most effective techniques are described below.

1) CENTROID LOCALIZATION

Centroid localization [175] has been proposed as an efficient localization method because it delimits the source of transmission of a message from the coordinates (x_i, y_i) obtained by averaging the coordinates of all receiving devices within reach.

The estimated coordinates of the NOI to be located are indicated as $p = (x, y)$, where each emitter R_i is located at a point with previously known coordinates $p_i = (x_i, y_i)$. The approximation of the x coordinates is calculated from all the coordinates of the receivers, and the coordinates are calculated from the y_i coordinates. Given a set of known points p_i in Euclidean space, for example, a number of receivers within the range of the transmitter, the calculation of the approximate location p of a node from the centroid of the known points p_i as shown in Fig. 15 can be performed using (21).

$$p = \frac{1}{n} \times \sum_{i=1}^{n} p_i, \tag{21}$$

where n = number of points within the range.

2) RECTANGULAR INTERSECTION

This technique is based on the idea of connectivity [57]. If two nodes can communicate, then one is assumed to be within a square centered on the other node, whose side is equal to two times the second's coverage radius. The algorithm's key advantage is that intersecting two squares is a mathematically simpler procedure than intersecting two circles. The simplicity arises from the fact that the result of two intersecting squares is a rectangle. Simultaneously, the intersection of circles is considerably more complicated. This geometric figure is described mathematically in Fig. 16.

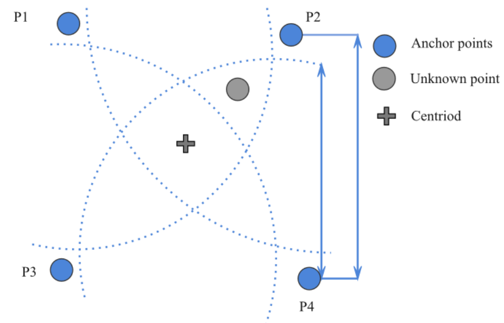

FIGURE 15. Illustrative example of centroid localization.

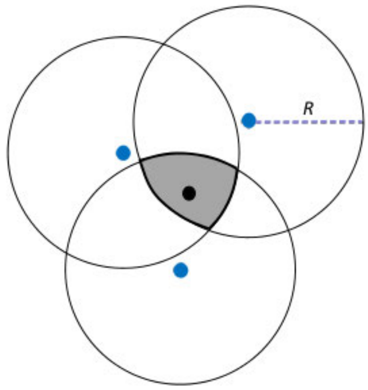

FIGURE 16. Circular intersection.

3) AMORPHOUS LOCALIZATION

The amorphous localization technique proposed in [58], [60] uses an algorithm similar to DV-Hop. For example, each node obtains the hopping distance to the beacon nodes by propagating messages. Once these messages are collected, distances are obtained by calculating local averages. Each node collects its neighboring nodes' estimated distances and calculates an average of all the neighbors' values. The coverage radius is then reduced and compensated for the errors caused by the low resolution. Such a system differs from the previous one when estimating average distance because it assumes that the network's density is known beforehand. In this manner, the mean distance of a jump can be calculated using the Kleinrock and Sylvester formula [61]. Finally, triangulation is used to estimate a node's position after obtaining the distances to three beacons.

4) APIT

In [55], APIT is a novel technique for finding the position of sensor nodes in a heterogeneous network, as shown in Fig. 17, where some sensors are equipped with GPS receivers. The beacons transmit messages, and an area-based technique is used to perform position estimation, in which the environment is isolated into triangular regions between beacons. The presence of a node within or outside these triangular regions enables a node to restrict the area in which it

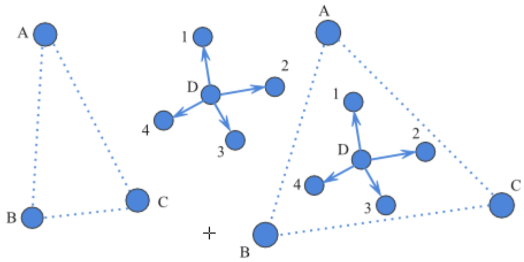

FIGURE 17. Illustrative examples of APIT.

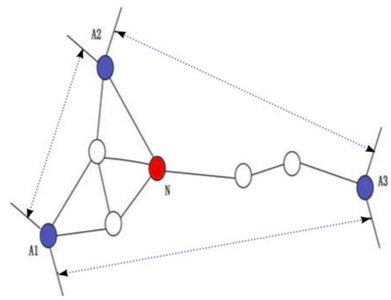

FIGURE 18. Illustrative example of the DV-hop technique.

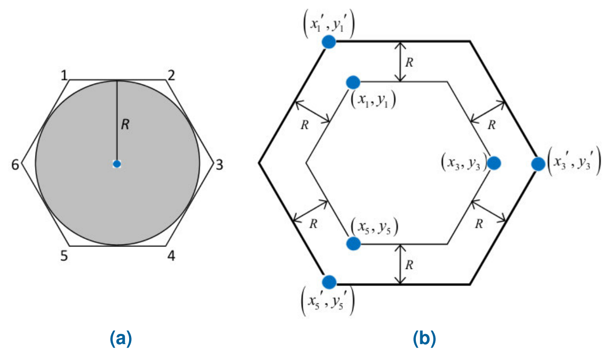

FIGURE 19. (a) Hexagon coverage approximation and (b) enlargement of pseudo-hexagon.

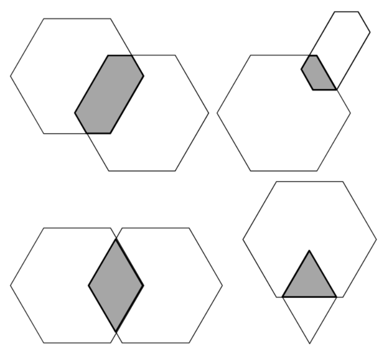

FIGURE 20. Hexagonal intersection.

can locate. The diameter of the estimated location in which a node locates can be reduced by using combinations of beacon positions, and thus, provide a better estimate of the position [62]. The theoretical technique used is called the point-in-triangulation (PIT) test [63], to restricts the possible position at which a node can reside. The calculated localization can be achieved using PIT, which can be optimized further to achieve more reliable results. A node selects three beacons and checks within the triangle created by the three beacons bound together in such a test. APIT performs a PIT test with various combinations of audible beacons unless all combinations are eliminated, or the predetermined accuracy level is reached. At such point, APIT estimates the center gravity of all the triangles in which a node is located to determine its location at its intersection.

5) HEXAGONAL INTERSECTION

The technique described in [64] is based on a rectangular intersection technique [65], namely, N-hop multilateration [66], [67]. It proposes the use of hexagons to represent the sensor coverage area. In particular, it uses a regular hexagon centered on a circular coverage area with an apothem of length equal to the coverage radius, as shown in Fig. 19. Although the result that iteratively intersects the rectangular region is always a new rectangle, the iterative intersection of these new rectangles will result in irregular polygons with three, four, five, or even six sides in the case of hexagonal areas, as shown in Fig. 20. However, such polygons exhibit the property in which all of them have inclination sides of 0°, 60°, or 120°. As the authors described, these pseudo-hexagons do not necessarily have six sides. If the coordinates of two opposite vertices form a rectangle, then a pseudo-hexagon requires the intervention of three vertices that belong to different sides. The vertices are numbered in a clockwise direction starting from the upper left vertex, i.e., vertices 1, 3, and 5.

The location process begins with the beacons, which broadcast their location pseudo-hexagon to their neighboring nodes. In the GPS receiver, the three vertices that determine a beacon's location pseudo-hexagon will coincide. Then, the nodes that receive the information from their neighboring beacons perform the intersection of the received pseudo-hexagons, enlarged by a factor equal to the sensor coverage radius. Therefore, such new pseudo-hexagons can be iteratively broadcast through the network, either upon reaching an initial established tolerance value or during a certain period. The authors of [68] demonstrated that the mere substitution of the geometric figure for representing the sensor coverage area reduces the location error by approximately 12%, with respect to the use of rectangles.

6) DV-HOP

The method proposed in [58] uses a mechanism similar to classic distance vector routing. In this system, a beacon broadcasts a message that contains the positions of all beacons with a hop-count. Each receiving node maintains the minimum value of the counter of each beacon among all the messages and disregards those whose counters are higher than the ones it has stored. Messages flow through the network from the inside out to increase the counter's value at each intermediate hop. Through this mechanism, all network nodes (including other beacons) obtain the shortest distance measured in hops, as shown in Fig. 18.

To convert the jump counter to a physical distance, the system estimates the average distance per jump without using distance-based techniques. Beacons perform this task by obtaining information about the position and hop counter of all the other beacons in the network. Once the average distances are calculated, the same beacons propagate this information to the other nodes. When a node can estimate the distance to more than three 2D beacons and four 3D beacons [59], that node uses the triangulation technique to estimate its position.

C. AI-BASED TECHNIQUES

1) ANNs

ANNs are a paradigm in machine learning and processing that are mathematically modeled for a specific problem and subsequently formulate a solution (program) by using a coded algorithm with a series of properties that allow the problem to be solved. Once the system is programmed to locate objects on the basis of the RSS received by the nodes, the system is entered, taking the position coordinates and the RSS as input. After training the neural networks, the appropriate weights are obtained. When a mobile device is in the area covered by these nodes, the position of the device can be obtained on the basis of the RSS received by the nodes and the weights acquired by the network during the training stage. The output of the system is a vector of two elements for a position estimated in 2D or a vector of three elements for a position estimated in 3D [173].

2) ANFIS

The architecture of the fuzzy inference system based on adaptive neural networks (ANFIS) is a neural model of adaptive networks that are functionally equivalent to fuzzy inference systems, allowing modulation by layers to facilitate the model training. Identifying the consequent parameters can be done with some least-squares method that leads to a prompt convergence of the model [179]. Although the ANFIS architecture can implement any fuzzy model, the first-order Sugeno model has been the most popular.

3) FUZZY LOGIC

Fuzzy logic is an extension of propositional logic. In which the truth value of the propositions extends to the fuzzy domain. So practically all the concepts of propositional logic apply to fuzzy logic. This work only discusses the Sugeno type inference machine of the first order based on the inference rule modus ponens of classical logic. A rule-based system is not a specific model for fuzzy systems; rather, it can be considered a general model that uses a granular approach. Because linguistic values can be defined by classical sets per set or with some granular computing technique [181]. Therefore, a fuzzy system can be classified as a granular computation technique, where membership functions define linguistic values, i.e., by fuzzy sets. The fuzzy system uses an inference machine to process the if-then rules and generate conclusions based on approximate reasoning, extending or generalising the modus ponens inference rule, deriving the inference from conclusions from the set of fuzzy rules approximate facts [179].

4) ANT COLONY OPTIMIZATION (ACO)

ACO is a novel technique in the category of metaheuristics [171], in which a colony of artificial ants cooperates to find reasonable solutions to discrete optimization problems. Cooperation is a key component of the ACO algorithm. ACO applies for classic problems finding their alternative solutions, such as the traveling salesman problem (TSP), and can dynamically adapt to changes in problem conditions. ACO can also be used in real problems related to routing, such as those encountered in parcel companies. The application of optimization methods based on colonies of ants is interesting because they exhibit versatility in different applications, such as

- Solving non-deterministic polynomial (NP-hard) problems, which cannot be solved by traditional exact algorithms.
- Solving dynamic problems that seek the shortest path. The properties of the problem change simultaneously with the solution being sought.
- Solving problems in which the computational architecture is spatially distributed.

5) PARTICLE SWARM OPTIMIZATION (PSO)

PSO is just one of many heuristic optimization strategies; a common alternative is genetic algorithms. Heuristic optimization does not have to be the most suitable form of optimization in all scenarios. It operates in the same way that a set of birds whose objective is to generate computational intelligence for searching corn utilizing social interaction rather only isolated movement cognitive abilities, i.e., direction, speed and acceleration with the behaviour of others. It is included in the evolutionary algorithms since the communications capacity of particles is thought to be an evolutionary and adaptive process [180]. Similarly, in PSO, the influence of the best possible position that has visited a particle across "species" mutation influences the particles' influence.

6) GRAVITATIONAL SEARCH ALGORITHM (GSA)

The authors in [178] designed the gravitational search algorithm (GSA) inspired by Newton's laws. However, it introduces some theoretical differences regarding the concept of mass and that of the universal constant of gravitation. Suppose we observe Newton's second law of dynamics, i.e., $\overrightarrow{F} = m\frac{d\bar{v}}{dt}$, F represents the exerted force on it, m represents the body's mass, and v represents the speed. It can be observed mass is the coefficient that measures

TABLE 1. Comparison of indoor positioning technologies.

Technology	Measurement mehtod	Range	Accuracy	Advantage	Disadvantage	Application
RFID [84-86,91]	Proximity detection, fingerprinting, trilateration, scene analysis	Up to 1000m	1m-5m	-High portability and Capability of providing both identification and location -Penetrates almost all types of material. -Larger range of frequencies.	-Affected by temperature and humidity.	-Indoor application
RFID/Bluetooth [87]	PDOA/Proximity/RSS	Up to 100m	Depends upon the range connectivity	Indoor coverage, low cost, low power consumption	One tag per location/object, low accuracy.	Indoor environment robot, industrial, logistics application etc. with higher frequencies
RFID/INS [88]	RSS/INS	Indoor	2m	-Operate in indoor environment - Control of the vehicle/robot,integrated navigation and guidance	- Cost such as maintenance cost, operation cost- Heat dissipation,navigation error increase over time	-Vehicle/robot, spacecraft, aircraft, missiles navigation
UWB [84,88,91]	AoA/ToA/ TDoATrilateration	10-15m	0.1-1m	-Transmit more information in less time-precision(12-36 in)	-Developing technology -Issues in NLOS -Short Range	-Indoor coverage applications with high accuracy
Zigbee [87,169,170]	RSS/PDOA	2.4 GHz	1-10m	-Indoor coverage, low power consumption, low cost	-Low accuracy	-Smart building (i.e.,indoor climate control,transportation and logistics, Object tracking, security & surveillance etc.
LANDMARC [88]	RSS, trilateration	50m	1-2m	-Improves the locating objects accuracy, higher tracking latency, energy efficient etc.	-Less efficient computationally, For its performance needs higher deployment density, tested in a small scale [24]	-User location sensing technology such as active RFID for the better accuracy.
Wi-Fi [85,91]	RSS-Fingerprinting, proximity, trilateration, angulation	Upto 20-50m	10-100m	-Indoor coverage, low cost	-Database required for fingerprinting, low accuracy	-To track indoor location, objects, assets
Infrared [85,86,91]	Proximity, trilateration	700m-1mm	1cm-5m	-Indoor coverage, Infrared devices are smaller	-It is not capable of going through walls or any kind of obstacle -It requires more sophisticated circuitry	-Outdoor application-active beacons/badge, thermal imaging
Bluetooth [84,88,91]	RSSI theoretical propagation model, RSS fingerprinting	Upto 100m	2-5m	-Consumption: low power, devices are relatively inexpensive	-Low latency, wireless interference, high density required, security vulnerabilities	-Use in indoor environment such as hospital, shopping mall etc.
NFR [87]	E.M near field characteristic	30-65m	1-5m	-Indoor environment, low cost	-Low frequency, large antennas	-RTLS solution for the indoor environment operation.
COMPASS [88,90]	RSS, trilateration	15m	1.65m	-Light weight and portable -Less sitting for fixing it on a station -Quickly determine the direction (minimum error in direction)	-Less precise in comparison of advance surveying method -Various errors, such as local attraction, magnetic meridian adjoining errors	-Protractor compass used for determining direction -Gyrocompass used for the true north -Smart phone due to magnetometer inside -Brunton Geo compass used by geologists
WhereNet [88]	RSS, trilateration	20m	2-3m	-Beneficial for the enterprise asset tracking and management -Accurately facilitate and locate number of vehicles etc	-Unidirectional transmitting, receiver costs, tag to receiver transmission only	-Automotive vehicle logistics.

''the body's resistance to acceleration'' produced by force and identifies with the body's inertia. On the other hand, as per the law of universal gravitation, i.e., $\|\overrightarrow{F}\| = G\frac{m_1.m_2}{r_2}$, G represents the proportionality constant and r the distance that separates them. The mass appears in two different forms; as an agent that generates the gravitational field and responds passively to the generated field. The direction of the force is the straight line that joins both bodies.

7) K-NN

A supervised classification method is used to estimate the density function $F(x/C_j)$ of the predictors x for each class C_j. In the case of scene analysis, this method is based on the momentary RSS value of the node to search for the k values or closest neighbors to this RSS value from a previously constructed database. Similarly, the approximate location is known. In such a case, k is the adaptation parameter for best performance, but it is fundamentally dependent on the data [173].

8) SMPs

SMPs are among the most widely used sets of algorithms for estimating position [168]. In this case, M positions are possible for each access point, the distance of which is established according to the momentary RSS compared with those stored in the database. Polygons of M vertices are formed to select at least one candidate for each access point. The smallest polygon has the smallest perimeter. The estimate of the signal position is obtained by calculating the average of the coordinates of the smallest polygon. SMP has been used for indoor localization.

9) SVMs

SVMs are a set of supervised learning algorithms for data classification and regression. They are used as a tool for statistical analysis and machine learning, and they work well in classification and regression applications. SVMs have been widely used for a wide range of applications in science, medicine, and engineering with excellent empirical performance. For example, several classes of support vector classifier (SVC) and support vector regression (SVR) have been used successfully in localization by digital identifiers [166], [167].

III. INDOOR AND OUTDOOR POSITIONING TECHNOLOGIES

These types of wireless technologies exhibit certain features and limitations that influence the signal. Dispersion, reflection, diffraction, and propagation are essential factors that influence signals [77], [159] along with the technology of maximum communication ranges, channel capacity, power consumption, regulations, intervention, safety and cost limit. Infrared, RF, and ultrasound are wireless technologies that are widely used for indoor positioning systems. Similarly, some indoor and outdoor positioning technologies are described below, as listed in Tables (1 and 2) and Fig. 21.

TABLE 2. Comparison of outdoor positioning technologies.

Technology	Measurement mehtod	Range	Accuracy	Advantage	Disadvantage	Application
GPS [88]	TDoA/ToA	Global	10-20m	-Earth scale coverage	-Outdoor coverage, expensive infrastructure	-Unmanned aerial vehicles (UAVs), aviation, marine, military, telecommunication.
A-GNSS [87]	TDoA	1500 MHz	<5m	-Country coverage	-Scarce indoor accuracy	-Unmanned vehicle, GIS, aerial photogrammetry, mining, machine control etc.
INS [87]	Angular rate, acceleration, earth magnetic field	1-5% of the travel distance-angle	10-100m	- Works everywhere	-Orientation/position drift, magnetic disturbance in indoor	-Spacecraft, tactical and strategic missiles,ships and submarines, aircraft,and robotics applications, dead reckoning
Galileo [87]	TDoA	1176-1207 MHz	1-5m	-Earth scale coverage, better positioning services	-Only outdoor, expensive infrastructure	-IOT L-band antenna, Soyuz rocket.
RADAR [88,89]	RSS, trilateration	Room scale upto 200f	2-3m	-To estimate and give the actual position of an object -To penetrate mist, fogs, snow	-Due to freely move of the radio signals in the space and air takes longer to an object	-Vehicle detection, air traffic control, missile control, moving target indication
LoRa [161]	RSS, trilateration	15-20km	14dBm	-Enable low-speed data communications over long distances -uses unlicensed radio spectrum in the industrial, scientific, and medical (ISM) bands to enable low-power -uses spread spectrum technology with a wider band etc	-Due to rules frequency band it utilizes, protocol doesn't allowed for its continous sending.	-Smart meters, inventory tracking, vending machines data and monitoring, automotive, and applications requiring data control and reporting

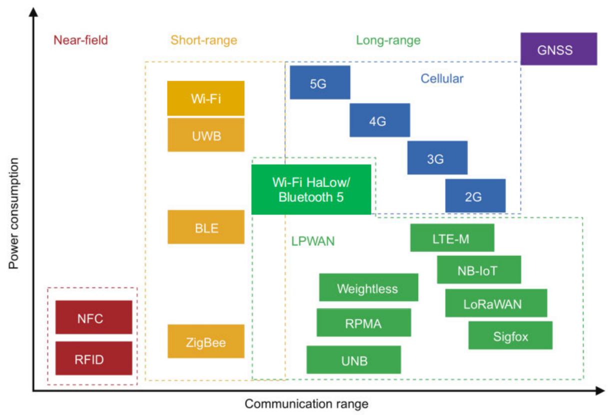

FIGURE 21. Comparison of the ranges and power consumption of some wireless technologies.

A. WIRELESS POSITIONING TECHNOLOGIES

1) WI-FI

A local wireless communication technology that is primarily aimed at accessing the Internet through a fixed access point or hotspot. In addition, Wi-Fi is a registered trademark of the Wi-Fi Alliance Company, which is responsible for testing and certifying that equipment with Wi-Fi technology complies with the IEEE 802.11 standard. The IEEE 802.11 (Wi-Fi) standards use the 2.4, 5, and 60 GHz bands to have a transfer rate within the order of tens or hundreds of Mbps, with a moderate range at the cost of high consumption [85]. This standard has several revisions or proposals: 802.11a, 802.11b and 802.11g, which are typically incompatible with one another.

In 2016, the Wi-Fi Alliance announced the release of Wi-Fi HaLow for products incorporating IEEE 802.11ah technology. HaLow operates in frequency bands below 1 GHz, enabling a wider range of lower-power connectivity than Wi-Fi certified products. In this manner, HaLoW allows a wide variety of energy-efficient applications, such as smart homes, car, digital health, industry, agriculture, and smart city environments.

HaLow expands Wi-Fi to the 900 MHz band, with low-power connectivity for wearable applications and sensors. The range is nearly double that of the current Wi-Fi. HaLow will not only transmit more signals, but it will also allow more robust connections in harsh environments where the capability to penetrate walls and other barriers is important. In addition, HaLow will adopt existing Wi-Fi protocols and offer numerous benefits to consumers [91]. Wi-Fi does not have a very high range, which would be counterproductive for a localization system that wants to discriminate between locations located at most tens of meters from each other. Wi-Fi technologies are experiencing a boom in deployment for indoor environments, such as hotels, cafes, airports, and other buildings. These new infrastructures also support object (people/things) localization and identification and making position-based applications for indoor environments viable [177].

2) INFRARED

Infrared wireless radiation technology is used in devices or systems that transmit data through infrared light. The companies Radiance and Versus use a combination of RF signals with infrared to obtain an object's position. Tags emit infrared and RF signals that contain a unique identifier for tracking objects or assets [78]. The use of RF allows for the most general positioning (e.g., floor), while infrared signals provide additional resolution (e.g., room). If another device receives the infrared signal transmitted by one device, then these devices are likely in the same location because infrared light does not pass through walls. Moreover, infrared light is reflected off the walls; therefore, the LOS between two devices does not necessarily have to be direct.

3) RFID

The RFID system is used to store and retrieve data through an integrated circuit's electromagnetic transmission via RF. It is used increasingly to improve data manipulation processes. The transmitted signal can penetrate nearly all types of building materials, and thus, it has an excellent range in indoor environments. Its propagation speed is also high, i.e., approximately 320 m/s. RF has restricted or unauthorized frequencies for telecommunications, allowing conditions for its free use. This type of series has the most extensive frequency range compared with infrared and ultrasound. Although propagation waves are within a higher frequency, interference with other components is less than those in other series. Nevertheless, interference does exist and is mostly due to ferromagnetic metals and radio emissions at close frequencies. However, it can affect various factors, such as temperature, humidity, or geometry of a building's interior side [79].

4) NFC

NFC [87] is a short-range wireless communication technology through which mobile devices can interact with one another at a distance of a few centimeters, where it is based on RFID. It uses variations in the magnetic field for data transmission and operates in the 13.56 MHz band. It has two operation modes: active and passive. Both devices generate magnetic fields in active mode, whereas only one device generates such fields in passive mode. Thus, in contrast with RFID, NFC can be used in two-way communication.

5) ULTRASOUND

Ultrasound operates at room level with high frequency. Ultrasonic positioning systems can estimate the position of objects at a sound propagation speed of 343 m/s. They exhibit good precision for localization. Ultrasonic positioning systems require users and objects or nodes to use certain ultrasonic tags. Such tags act as transmitters or receivers; one tag will be in motion while the other will be stationary or fixed [80]. The advantages of ultrasound devices are their simplicity, inexpensive and low cost. However, ultrasound may face difficulty to penetrate walls due to its signals influences but appropriate for indoor localization [81].

6) GPS

GPS works through a network of 24 satellites orbiting the Earth at an altitude of 20,200 km, with synchronized trajectories to cover the Earth's entire surface [82]. To determine position, the receiving device can capture information from at least four satellites in the network, from which it receives signals that indicate their position at each clock. On the basis of such signals, the GPS receiver synchronizes the clock and calculates the distance to the satellite via signal delay, i.e., the ToA.

In contrast with the 2D case, triangulation in the case of GPS consists of finding the angle with respect to known points based on each satellite's distance from the measurement point. This process can easily determine the relative position of the satellites, where each signal's coordinates occur, and the real coordinates of the measurement point are obtained. Real accuracy is achieved in the GPS clock, which is similar to the atomic clocks that synchronize satellites from the ground.

7) RADAR

The Microsoft research team developed RADAR, a building location and tracking system based on IEEE 802.11 WaveLAN technology [83]. In a base station, RADAR measures the RSS level and signal-to-noise ratio of signals sent by wireless devices. This information is used to calculate 2D positions within a building. Scene analysis and multilateration are the techniques used for localization. RADAR uses the same infrastructure for wireless networks in a building with few base stations. RADAR has two disadvantages. First, the tracker must support a wireless local area network (WLAN), which is impractical for small devices or those with limited computing capacity. Second, scaling the system to three dimensions for multi-story buildings presents a nontrivial problem.

8) BLUETOOTH

Bluetooth is a short-range radio wave wireless technology that operates in the Industrial, Scientific, and Medical (ISM) frequency band. Its latest version, 4.0, allows up to 24 Mbit/s transmission rate, which does not require a license and is specifically between 2.4 GHz and 2.485 GHz. Bluetooth is the common name for the IEEE 802.15.1 specification, which defines a global standard for the transmission of information (voice and data) wirelessly between different devices over a secure and license-free short-range RF link [84], [91].

9) ZigBee

Zigbee is the name given to a series of protocols based on the IEEE 802.15.4 standard, which was designed to create wireless communication networks with low data transfer rates, working at different frequencies between 868 MHz and 2.4 GHz [169], [170]. Zigbee-based networks are popular at present, particularly for home automation applications, because of the following reasons.

- They have extremely low consumption because they spend most of their time "sleeping". This feature makes them an attractive alternative to Bluetooth networks.
- They are mesh networks, where each node communicates with other nodes directly and with the base station, in contrast with Wi-Fi technology that requires a central node to manage communications.
- The nodes can be manufactured using small electronics in a simple and inexpensive manner, and thus, they can be extremely small and functional.

The most widely used communication frequency (and the only one worldwide) is 2.4 GHz, which supports transfers of up to 40 Kbps on 16 different channels. Zigbee also works at 915 MHz (in the USA, 20 Kbps in 10 channels) or 868 MHz (in Europe, 20 Kbps in a single channel). Zigbee is a leading technology in its target market. It is the only wireless communication technology that focuses on environmental monitoring and data sampling by using sensors, optimizing consumption and cost [169], [176].

10) LoRa

LoRa, short for long range, is a specification for a low-power wide area network (LPWAN) proposed by the LoRa Alliance [161]. It is intended for the communication of low-cost, low-power, and battery-powered devices. The specification covers the physical layer and access to the network medium, leaving the remaining layers to the applications [176]. The communication between the devices and the base stations (called gateways by the specification) is based on the LoRa modulation developed by the Semtech Company (Semtech, 2015a). This modulation allows links of several kilometers even in urban environments due to its maximum link budget of 155 dB, with a bit rate between 0.3 kbps and 50 kbps.

Regarding the particularities of LoRa modulation, different devices emitting on the same frequency but with varying bit rates do not corrupt transmissions. This feature makes having a large number of virtual channels for communication between end devices and the base station possible.

11) SIGFOX

Sigfox [172] is an LPWAN network operator that offers end-to-end Internet of things (IoT) connectivity solutions based on its proprietary technologies.

- It implements its proprietary base stations equipped with software-defined cognitive radios and connects them to back-end servers via an IP-based network. The end devices connected to these base stations use binary phase-shift keying (BPSK) modulation and demodulation on an ultra-narrow band (100 Hz) sub-GHz ISM band carrier.
- It uses unlicensed ISM bands, e.g., 868 MHz in Europe, 915 MHz in the USA, and 433 MHz in Asia. Sigfox uses the frequency bandwidth efficiently and experiences extremely low noise levels by using a narrow band, leading to very low power consumption, high receiver sensitivity, low-cost antenna design, and a maximum throughput of only 100 bps (SIGFOX, 2020).
- It initially supported uplink communication, but it was later transformed into a bidirectional technology with link asymmetry. Downlink communication, i.e., data from base stations to end devices, can only occur after uplink communication. The number of messages over the uplink is limited to 140 12-byte messages per day (IoT Factory, 2020).

B. LOCALIZATION AND IDENTIFICATION APPROACHES BASED ON RFID SYSTEM

Object identification and localization can address more than an intelligent environment's real-world problem [109]. Hence, this work uses such type of system to identify and localize objects (things or humans) and maintain the signal strength of an RFID system toward a targeted object. The localization and identification techniques presented in [110] consider various RF technologies, such as UWB and Wi-Fi. Hence, such a system can identify and localize multiple objects, whether standing, walking, and occluded in an environment. Previous RFID-based localization research depended mostly on AoA or RSS to achieve an actual object position. Throughout the literature, multiple configured sensors have been used to map 2D object locations [111], and researchers have incorporated and measured the efficiency of the best probabilistic multiple hypothesis tracking methods. In these methods, the outcome represents the same tracking efficiency. In [112], such approaches were widely used to address indoor localization modeling, which is based on outdoor modeling.

Compared with outdoor modeling, indoor localization is more challenging when estimating computational modeling. Indoor localization has suggests many solutions. Some of the techniques are a global navigation satellite system (GNSS) and its subcategories, namely assisted (AGNSS) and differential (DGNSS). However, the simplified probabilistic method exhibit have a high risk of failure without a practical outcome. Thus, this method can be enhanced using a complex probabilistic model.

In addition, [113] introduced models of similarity, relying on a racially discriminatory look to identify and localize multiple objects/people from a single camera in a complex scenario. Many robust multi-object identification and localization methods were explained in [114], [115] based on navigation-by-detection. In [116], the authors addressed the multi-object localization problem by using the LRF equipped on a service G5 robot.

The authors of [117] suggested that an RFID-based system may be used to retrieve and identify the location data of an object. In [118], a mobile robot was configured with RFID antennas and a LiDAR sensor that can read tags and collect information. In [119], an external camera with a combination of RFID tags was used in robot monitoring. Vision-based and LiDAR sensors are extensively used in indoor environments [120], [121]. A sensor model is frequently used in such an experiment to estimate and measure dynamic object location at a certain time of the identified tags, which are worn by any object in the coverage area.

Different methodologies and technologies were reviewed in [122] for indoor and outdoor localization, and a comprehensive study was presented in terms of scalability, cost, security, accuracy, and complexity. Many indoor localization and identification techniques were introduced in research to improve localization accuracy, and they can be categorized into detection and tracking, proximity, and distance measurement [123]. Position estimation algorithms utilize various methods for measuring range, such as ToA, TDoA, and RSS, as described in Section 2.

1) RADIO SIGNAL TAG LOCALIZATION AND IDENTIFICATION

The utilization of radio signals opens the possibility of adopting RFID readers equipped with antennas on a robot/vehicle. The scene will envision a multi-object equipped with RFID tags in a certain environment to identify and localize tags, as shown in Fig. 22. Such tags can initially be in active mode

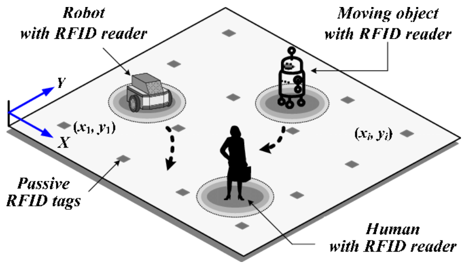

FIGURE 22. RFID-based localization environment.

for the reader by transmitting a radio signal, e.g., an unmodulated ultrahigh-frequency (UHF) carrier [124] or a dedicated signal that utilizes high-directivity antennas.

Initially, a possible technique is to identify and detect a tag and subsequently create a reader–tag communication link, broadening the fixed beam analysis [125] by considering the beam steering activity for localization. Moreover, a scheme that enables tags to be detected, communicated, and located by processing the backscatter response from an appropriate interrogation sensor signal sent by the reader is considered.

C. LOCALIZATION AND IDENTIFICATION APPROACHES BASED ON MULTIMODALITY

The primary objective is to identify and localize multiple objects autonomously, and unique sensor-based systems are sufficiently applied across various spaces [126] efficiently and effectively. In [127], [134] depth camera sensors were used for the solution to track and localize household objects. Moreover, some spaces cannot be restricted to indoor environments, making the issue more confusing. High reliability is an additional criterion, and such systems will have a wide range of sensor modalities. Sensor fusion is essential for achieving the requirements of such systems. Some sensors have different spurious measurement forms (e.g., radar, ultrasound, vision, LiDAR, and GNSS) [157].

1) EFFECT OF DIFFERENT SENSOR MODALITIES

Radio signals captured through an RFID antenna mounted on a robot provide effective signals to its surroundings [128]. Inside buildings, different wireless sensors, such as RFID, Bluetooth, and WLAN, provide localization accuracy ranging from several meters to centimeters. In [129], an energy-efficient positioning method, namely, Bluetooth-based position synchronization (BPS), was proposed. Through a Bluetooth connection using BPS, location data are shared among various devices/sensors. To retrieve higher-level semantic data, such as identification and localization, various clustering and classification methods are applied, including k-NN and hidden Markov model (HMM) for the signals. The integrated system evaluates the movements of dynamic multiple objects [100] to enhance identification accuracy.

As mobile devices become more ubiquitous and highly efficient, face and speech recognition methods that can be used on mobile devices were also discussed [130]. In [131], current SLAM technologies, LiDAR, and vision sensors were commonly used. Therefore, visual systems are sensitive to illumination and a dynamic environment, where dynamic and transparent objects are also affected by LiDAR sensors [158]. In [132], an indoor location system was suggested by combining Kinect and active RFID with the recognized positioning features and Kinect object retrieval capability. For communication purposes, the RFID system uses electromagnetic waves, which are reliable for complex object disturbance and illumination conditions. Rao-Blackwellized particle smoothing (RBPS) was suggested in [133] with an ultrasound sensor for occupancy grid-based SLAM. In [135], the authors presented an integrated system that uses face and voice recognition, such as motion sensors. These technologies exhibit novelty for interpreting a specific modality product by using a particle filter to incorporate all techniques for presenting robust identification and localization.

2) EFFECTS OF ACCELEROMETER AND LRF SENSOR

The literature proposed to fuse wearable accelerometers with navigation and the navigation of objects identified using laser sensors to recognize and locate multiple objects [136]. The authors first identified the motion signatures of a person's gait for each object in a scene by using this method. The moving object (human) is also wearing an accelerometer for the identification of motion signatures. For matching purposes, clustering is applied to detection, while tracking signals and a laser scanner are also applied to the accelerometer to resolve localization. Thus, each accelerometer is combined with a unique ID, making identification simpler.

The authors of [137] proposed emerging camera-based existing infrastructure with other sensors, such as magnetometer and accelerometer integrated into a person's mobile phone to overcome a certain problem [138]. In this approach, the sensor detects every object's position, which is wirelessly communicated to any mobile device of the user. Mobile phones solve the possible location after receiving the positioning information by comparing those with their sensors' measurements. Identification is extremely easy with this method. Each object is identified with its unique tag ID worn by the user.

3) EFFECTS OF RFID AND LRF SENSOR

Although the RFID system for identification is nearly accurate, the literature proposes the combined use of an LRF sensor and an RFID system to obtain accurate results apart from localization. Single and multi-RFID antennas were proposed in [139] to measure and compare multi-path channel fading, given that the Rician distribution was used to design the RFID channel fading in [140] for successful tag detection. The RFID technologies in [141], [142] provide a measurement mechanism for identification and localization. The field of sense (FOS) and field of view (FOV) techniques are widely used for unknown environments.

In addition, RFID recognition systems are also incorporated with sensor technology to evaluate each person's position in a minimally intrusive manner. The method computes every person's location uncertainties from the provided signal strength and includes closest neighbor techniques to map each identified object position through the sensor. Such existing systems measure the relative or absolute position of the objects with higher accuracy by using the phase attribute [143].

IV. LOCALIZATION AND IDENTIFICATION METHODS

The purpose of identification and localization methods is to determine the location of object (people/things) that occurs during navigation. The means to classify these methods are varied and must satisfy different criteria. A possible classification is to group these methods into local or global, active or passive, static or dynamic depending on the environment [100].

Other approaches focus on the type of environment map used, i.e., topological or metric maps, in methods based on landmarks or probabilistic methods. Each group is not exclusive because some localization methods may belong to several groups. Different localization and identification methods are described as follows, with special emphasis on landmark-based and probabilistic methods.

1) *Local or Global Methods:*
Local localization methods require the initial location of a robot to be known because they can only follow a robot's position. The objective of these local localization techniques is to correct the lag in a robot's position due to errors related to odometry, a consequence of any type of objects movements [100], [101].
By contrast, global location methods enable determining a robot's position without any information regarding its initial position. This type of technique exhibits two important advantages over local methods. First, knowing the initial location of a robot is not required. Second, these techniques are more robust because recovering a robot's position from false positions is possible. Despite the advantages of global methods over local ones, the latter methods are more frequently encountered due in part to their lower complexity.
2) *Active and Passive Methods:*
Active localization assumes that the algorithm in charge of performing the task has total or partial control of the robot during the localization process, increasing the process's efficiency and robustness [102]. In passive localization [103], [160] the localization algorithm works exclusively with the data provided by the sensors. All other considerations, such as the robot's movement, cannot be controlled. Most methods are passive in nature.
3) *Static and Dynamic Environments:*
This classification considers the nature of the environment. Static environments such as those in which the entire environment distribution is fixed in time. The only parameter that can be varied is the location of the robot [104]. However, most environments are dynamic because their appearance or layout can change significantly. For example, pieces of furniture can change places in a room, doors or windows can be opened or closed, and another mobile robot may exist in the same environment.
4) *Metric and Topological Methods:*
As explained in Section 2.4, the map of an environment can be represented in different ways. In turn, a map also represents a criterion for classifying localization methods. We can distinguish between metric and topological methods. Metric maps describe the environment as a set of objects or occupied positions in space. Topological maps, which use an environment graph, represent connectivity between different regions [105].

A. LANDMARK-BASED METHODS

These methods are based on the recognition of landmarks, which represent characteristic points of the environment, as a reference for determining a robot's location [106]. To achieve this objective, a mobile robot must be equipped with a sensory system to collect information from the environment, such as artificial vision, ultrasound, and infrared sensors.

Once these landmarks are detected, they are compared with the information available about the environment. The robot's position is then determined by applying techniques, such as triangulation. Thus, this localization method can be divided into four phases, as shown in Fig. 23.

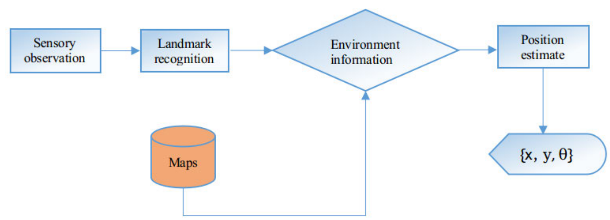

FIGURE 23. Landmark-based robot location phases.

Localization by landmarks can be classified in accordance with natural landmarks in the environment. These landmarks can be active or passive [102], [103]. The latter can be further subdivided into, which can be artificial or natural landmarks, as shown in Fig. 24.

1) ACTIVE LANDMARKS

Active landmarks are those that emit a certain type of signal that informs about their location. Examples include the satellites of GPS systems, ultrasonic beacons, radio beacons, and magnetic dipoles [102]. The most widely used system is GPS. The United States Department of Defense set out to create a more precise navigation system that would supersede the systems available at that time. These systems were based on the Doppler effect, which uses the frequency variation of

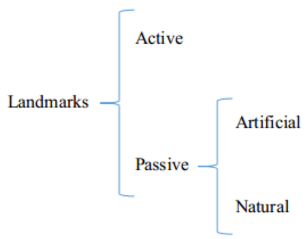

FIGURE 24. **Landmark: active and passive.**

radio signals transmitted by satellites, such as the TRANSIT system.

The GPS system works through a network of 24 satellites in 6 orbits over the globe at an altitude of 20,200 km, with synchronized trajectories to cover the entire Earth surface. To determine position, a receiver is used to locate at least three satellites automatically in the network. It receives signals that indicate the identification and clock time of each satellite [107]. On the basis of these signals, the device synchronizes the GPS clock and calculates the time it takes for the signals to reach the equipment. In this manner, distance to a satellite is measured using triangulation (inverse trilateration method), which is based on determining the distance of each satellite from a measurement point. Once the distances are known, your relative position with respect to the three satellites can be easily determined. The absolute position or real coordinates of a measurement point are obtained when the coordinates or position of each satellite is determined through the signal they emit.

2) PASSIVE LANDMARKS

These landmarks are based on the recognition of objects that belong to the close environment of a robot. They do not actively emit any signal. Consequently, a robot search actively for these landmarks through its sensors to execute the subsequent location process. These landmarks must be referenced on a global map of the terrain and known beforehand to determine a robot's absolute position [103]. As discussed previously, passive landmarks, depending on their nature, can be artificial or natural.

- *Artificial Landmarks*: They are intentionally placed in a work environment such that they are visible to a robot's sensors [108]. They are used when a robot develops its indoor actions. Existing artificial landmarks include barcodes and geometric figures.
- *Natural Landmarks*: [103] Natural landmarks are part of the environment where a robot moves. The method that uses these landmarks is more complex than the previous case because natural objects must be detected and identified, and the landmarks to consider must be determined. Therefore, the objects' characteristics must be extracted using descriptors that determine the suitability of each of them. In indoor environments, natural objects can include doors, windows, and lamps. In outdoor environments, examples include trees, traffic signs, and roads. Finding feature points is more complex outdoors than indoors.

The major disadvantage of these landmarks is that the further away a robot is from them, the less adjusted and accurate the estimate will be. Moreover, when comparing passive landmarks with active ones, the former poses more difficult during detection and requires a considerable amount of processing to identify.

B. LOCALIZATION AND IDENTIFICATION BASED ON PROBABILISTIC METHODS

In classical methods used in robotics, the algorithms' success depends fundamentally on two aspects: the precision of the robot's sensors and the accuracy of the models of the environment and the robot. However, fulfilling these two conditions does not guarantee complete success because errors and uncertainties will always occur in a real field. Here, we highlight the major adversities.

- *Sensor Noise*: Observations made by normally noisy sensors and the statistical distribution of such noise are frequently difficult to model [144].
- *Position Detection Noise*: A robot's movements are typically not exact, nor are they detected precisely via odometry. Odometry errors are also cumulative. Small errors in a robot's rotation can exert important effects on estimating its translational movements and determining its final position [145].
- *Complex and Dynamic Environment*: Indoor environments in which robots move are usually complex and dynamic, and thus, maintaining consistent models is difficult.

Considering these problems, probabilistic methods or approaches have been demonstrated to offer more robust results than classical methods. The latter is attributed to the fact that probabilistic methods are supported by models that represent information through probability functions, making them more robust in the face of sensor limitations and noise in robot kinematics. However, the most cited limitations of probabilistic algorithms are computational inefficiency because all the probability distributions of a robot's position space must be considered and the inherent necessity of discreetly approximating the continuous reality of the robot context [146].

1) SOLID BASED ON BAYESIAN APPROACH

The general localization problem can be described as a Bayesian estimation problem [147], [148] for SOLID [162], where estimating an object location given a set of noisy measurements is desired. Thus, observing the issue in a probabilistic manner based on all the available information provides the robot with a certain degree of confidence or certainty (belief) about the place where it is located. Then, the location problem consists of estimating the probability density of a robot's location. A Bayesian framework that estimates this density is Markov localization [149], which combines the information from absolute and relative sensory measurements to obtain probability density.

a: PROBABILITY THEORY

1) *Probabilistic Model Performance in Localization and Identification:*
An object or a robot that navigates in its environment takes action to change its position. Suppose u_t is defined as the action performed by the object/robot at instant t. In that case, a probabilistic model that expresses the way the object/robot's location changes is the transition density.

$$P(x_t|x_{t-1}, u_{t-1}), \tag{22}$$

In (22), x_{t-1}, and x_t represent an object or a robot previous and final states, and the action of a robot represents as u_{t-1}. The transition density describes how the robot's actions change its location. This density is known as the performance or movement model. In practice, it can be approximated from the robot's kinematics.

2) *Probabilistic Measurement Model:*
Let Z be the set of all possible measurements from a sensor, and let z_t be an element of Z observed at time t. The probability that a sensor observes z_t from a certain location x_t can be described by the density [150].

$$P(z_t|x_t), \tag{23}$$

which is known as the perceptual model.
This probability density is difficult to calculate due to the high dimensionality of sensory measurements. However, a possible solution was proposed by Rana *et al.* [151], who used a feature extractor based on the k-NN algorithm to project a set of raw sensory data from space S to a lower-dimensional feature vector in Z space ($\sigma : S \rightarrow Z$). Thus, the probability density represented in (23) is regarded on the basis of the Z feature vectors rather than the Z sensor's raw data. An example of the proposed technique is found in localization and identification methods based on landmarks [152]. A feature vector extracted from sensory data may contain only the absence or presence of landmarks, omitting the remaining sensory data stream's information. Another example is that of localization and identification methods based on model matching [153], where partial models, such as feature maps, are extracted from sensory data and then compared with a model of those existing in the environment. From the preceding discussion, the densities obtained do not relate the raw data flow of the sensor to the various locations in the environment but rather relate the characteristic vectors to them.

3) *Markov Localization Algorithm:*
An object or a robot is assumed to have initial confidence regarding its location $P^+(x_0)$. At every instant t, the robot performs an action u_t that ends when the next time slot begins. This action changes the state of the robot in accordance with (22) and (24), and thus, its confidence evolves to $P^-(x_t)$. As the robot moves, the probability distribution is updated to consider the added uncertainty in the robot's position due to, for example, odometry errors. The confidence that the robot gains after incorporating the action u_{t-1} and a new vector of measures z_t is known as a priori confidence [154].

Algorithm 1 Bayesian or Markov Localization Algorithm

$Markov\_localiza\ (P^+(x_{t-1}), u_t)$
//for all possible $x_t\, do\{$
//predict trust
$\quad P^-(x_t) = \int P(x_t|x_{t-1}, u_t)P^+ = P(x_{t-1})dx_{t-1}$
//observe the environment and extract characteristics
$\quad z_t = Z(\sigma : S \rightarrow Z)$
//update trust
$P^+(x_t) = \eta_t P(z_t|x_t \int P(x_t|x_{t-1}, u_t)P^+ = P(x_{t-1})dx_{t-1}$
$\quad returnP^+(x_t)\}$
$\quad t = t - 1$
$\quad goto(1)$

$$P^-(x_t) = P(x_t|z_1, u_1, z_2, u_2, \ldots, z_{t-1}, u_{t-1}), \tag{24}$$

In addition, the authors of [155] reported that a robot could also acquire information by observing the environment with its exteroceptive sensors. Here, you may extract characteristics from this information to form a vector $z_t = \sigma(s_t)$, which is distributed in accordance with the probability distribution in (23). In the next step, the robot updates its $P^+(x_t)$ confidence with the new information to better estimate its location as given in (25). Once the robot receives an absolute measure z_t at instant t, it incorporates this measure to obtain the posterior confidence.

$$P^+(x_t) = P(x_t|z_1, u_1, z_2, u_2, \ldots, z_{t-1}, u_{t-1}, z_t), \tag{25}$$

Bayesian localization models the user's position at time t. x_t is a random variable whose probability distribution $P(x_t)$ is estimated from the set of measurements received up to the current time: $z_1, z_2, \ldots, z_t$, as shown in (26).

$$P(x_t) = P(x_t|z_1, z_2, \ldots, z_t) \tag{26}$$

The RFID system is described in detail in this review. The z_t measurements correspond to the signal strength readings from different RFID beacons received in the time interval $t - 1$ to t.
The estimate of the probability density $P(x_t)$ is iteratively updated over time in two stages, i.e., prediction and correction. During the prediction stage, the current position is calculated from the previous position $t - 1$.

The so-called movement model is given in (27).

$$P^{-}(x_t) = \int P(x_t|x_{t-1}, u_{t-1})P(x_{t-1})dx, \qquad (27)$$

where the minus sign indicates that the estimate obtained is a priori (concerning the experimental measure), and the variable u_t represents sensory information about the user's movement. For example, odometric measurements of the robot's wheels in the case of a mobile robot, while measurements can be made using inertial sensors for the movement of a person.

After the prediction stage, the correction stage measures the correspondence between the expected sensory measurements in the estimated position and those received experimentally z_t. According to Bayes' theorem, the posterior probability is obtained as shown in (28).

$$P^{+}(x_t) = a_t P(z_t|x_t), P^{-}(x_t), \qquad (28)$$

Multiplying the previous probability so-called observation model $P(z|x)$, that quantifies the receiving measurement z in case the user is in position x. The observation model must be generated prior to the estimation process from a set of empirical measurements that can be obtained experimentally at different points in the workspace. In (23), a_t is introduced as a normalization constant, i.e., the integral of the probability over the entire region of possible displacement.

For the term $P(z|x)$ used in (27) and (23), z_t corresponds in general to several individual measures $z_t^1, \ldots, z_t^n$ from different sensors and received at the interval $t-1$ to 1. Calculating the joint probability of these measures is mathematically complicated, and thus, we will assume that the measures z_t^j are conditionally independent as given in (29).

$$P(z_t^1, \ldots, z_t^n|x) = \prod_{j=1}^{n}, P(z_t^j|x), \qquad (29)$$

(27) and (28) are applied consecutively at each time interval t. Under normal circumstances, the probability distribution given by (29) will be concentrated around the actual position of the object after a few iterations.

V. CONCLUSION AND FUTURE SCOPE

State-of-the-art positioning technologies and techniques for indoor and outdoor environments have been reviewed and analyzed in this paper. Various critical challenges for identifying and localizing dynamic multiple objects with multi-sensor and multifunctional techniques have also been presented. Current technologies, such as RFID, LRF, and other sensors with in-depth analysis, have been emphasized for moving object identification and localization. Range, accuracy, measurement method, advantages, disadvantages, and applications have been compared in detail. This paper has also presented state-of-the-art multimodal data fusion techniques through probabilistic methods that estimate moving object identification and localization more precisely. These techniques have been applied to mobile robots and other dynamic moving objects. The performance of emerging technologies may provide less invasive methods that can further improve the localization of moving objects. This review can provide guidance for readers in the localization and identification field where each category of methods, their advantages, and solutions have been fully explained. In addition, many important localization and identification techniques and technologies have been formulated to achieve improvements and address limitations in future research.

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RASHID ALI received the B.S. degree in computer science from the University of Balochistan, Quetta, Pakistan, in 2011, and the M.S. degree in software engineering from Hamdard University, Karachi, Pakistan, in 2019. He is currently pursuing the Ph.D. degree with the School of Information Engineering, Southwest University of Science and Technology, Mianyang, China. Since 2013, he has been a Lecturer with the Department of Computer Science, University of Turbat. He has authored more than five articles. His research interests include AI (robotics), multi-sensor, and vehicle/object indoor positioning and localization.

RAN LIU received the B.S. degree from the Southwest University of Science and Technology, Mianyang, China, in 2007, and the Ph.D. degree from the University of Tüebingen, Tübingen, Germany, in 2014, under the supervision of Prof. Dr. A. Zell and Prof. Dr. A. Schilling. His research interests include robotics, indoor positioning, and SLAM.

YONGPING HE received the B.S. degree from the Southwest University of Science and Technology, Mianyang, China, in 2018, where he is currently pursuing the M.A.Sc. degree. His research interests include SLAM and UWB positioning.

ANAND NAYYAR received the Ph.D. degree in computer science in the area of wireless sensor networks and swarm intelligence from Desh Bhagat University, in 2017. He is currently working with the Graduate School, Duy Tan University, Da Nang, Vietnam. He is also a Certified Professional with more than 75 professional certificates from CISCO, Microsoft, Oracle, Google, Beingcert, EXIN, GAQM, Cyberoam, and many more. He has published more than 450 research papers in various national and international conferences, and international journals (Scopus/SCI/SCIE/SSCI Indexed) with high impact factor. He has authored/coauthored cum edited more than 30 books of computer science. He has five Australian patents to his credit in the area of wireless communications, artificial intelligence, the Internet of Things (IoT), and image processing. His current research interests include the area of wireless sensor networks, the IoT, swarm intelligence, cloud computing, artificial intelligence, blockchain, cyber security, network simulation, and wireless communications. He is a member of more than 50 associations as a Senior Member and a Life Member and also acting as an ACM Distinguished Speaker. He was awarded more than 30 awards for teaching and research–the Young Scientist, the Best Scientist, the Young Researcher Award, the Outstanding Researcher Award, Excellence in Teaching, and many more. He is associated with more than 500 international conferences as the programme committee member/chair/advisory board/review board member. He is acting as an Associate Editor of *Wireless Networks* (Springer), *IET Quantum Communication*, *IET Wireless Sensor Systems*, *IET Networks*, *IJDST*, *IJISP*, and *IJCINI*. He is acting as an Editor-in-Chief of IGI-Global, USA journal *International Journal of Smart Vehicles and Smart Transportation* (IJSVST).

BASIT QURESHI (Member, IEEE) received the bachelor's degree from Ohio University, Athens, OH, USA, in 2000, the master's degree from Florida Atlantic University, in 2002, and the Ph.D. degree from the University of Bradford, U.K., in 2011, all in computer science. He is currently an Associate Professor and the Chair of the Department of Computer Science, Prince Sultan University, Saudi Arabia. He has published over 60 research works in the area of robotics, the Internet of Things, machine learning, and computational intelligence. He is a member of the IEEE Computer Society, the IEEE Communications Society, and the ACM.