A Survey on Device-free Indoor Localization and Tracking in the Multi-resident Environment

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Indoor device-free localization and tracking can bring both convenience and privacy to users compared with traditional solutions such as camera-based surveillance and RFID tag-based tracking. Technologies such as Wi-Fi, wireless sensor, and infrared have been used to localize and track people living in care homes and office buildings. However, the presence of multiple residents introduces further challenges, such as the ambiguity in sensor measurements and target identity, to localization and tracking. In this article, we survey the latest development of device-free indoor localization and tracking in the multi-resident environment. We first present the fundamentals of device-free localization and tracking. Then, we discuss and compare the *technologies* used in device-free indoor localization and tracking. After discussing the steps involved in multi-resident localization and tracking including target detection, target counting, target identification, localization, and tracking, the *techniques* related to each step are classified and discussed in detail along with the performance metrics. Finally, we identify the research gap and point out future research directions. To the best of our knowledge, this survey is the most comprehensive work that covers a wide spectrum of the research area of device-free indoor localization and tracking.

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CCS Concepts: • **General and reference → Surveys and overviews**; • **Human-centered computing → Ubiquitous and mobile computing**;

Additional Key Words and Phrases: Device-free, indoor localization, indoor tracking, multi-resident, non-intrusive

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1 INTRODUCTION

Indoor localization and tracking aims to estimate the current location of a person using a suitable device and predict this person's next locations from time to time in indoor areas such as residential

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homes and office buildings. This area of research has become crucial for applications in healthcare [1], energy management [2, 3], and security management [4]. For example, a monitored or elderly patient can receive prompt assistance in emergencies such as falling, parents can be alerted if their children enter potentially hazardous areas, and rescuers can be informed with whereabouts of rescuees in a building to formulate appropriate rescue plans. Several indoor localization and tracking approaches and systems have been proposed in recent years. Some solutions require occupants to wear or carry localization and tracking devices such as radio tags and mobile phones [5–7]. However, it is not always convenient for occupants to carry tracking devices in residential homes or offices, and there is always a chance that the devices are misplaced [1, 8]. However, device-free localization and tracking solutions can overcome these drawbacks, and there are various types of technologies that can be used such as radio frequency (RF) [9, 10], surveillance cameras [11], infrared [12–14], acoustic [15], and electric field [16].

Among the device-free approaches, the surveillance camera-based solutions have been used extensively [11, 13]. However, camera surveillance may not be appropriate for private spaces such as offices or homes. However, non-intrusive sensing technologies, such as passive infrared and radio frequency, can sense the presence of a person without revealing his or he identity or appearance and thus are more appropriate for privacy-sensitive settings.

Among the existing surveys on device-free indoor localization, Palipana et al. [17] provided a detailed review of device-free localization based on RF technology. Liu et al. [18] proposed a classification of the wireless localization and tracking techniques. Xiao et al. [19] classified indoor localization from the device perspective. Different from these works, we also provide a comprehensive review on the technical aspect, which includes the methods and algorithms, of the selected device-free indoor (DFI) localization and tracking approaches with a special focus on approaches for the complex multi-resident environment. In recent works, Gu et al. [20] focused only on techniques to improve the localization based on spatial information. Khelifi et al. [21] provided a general overview of localization systems and their applications in the IoT environment. We provide an in-depth review of techniques for localizing and tracking multiple persons.

The main contributions of this work are as follows:

(1) We provide the complete picture of DFI localization and tracking as well as the taxonomy and classification of related DFI localization and tracking techniques.
(2) We present the detailed steps of the DFI localization and tracking process and discuss and evaluate the corresponding techniques including those for the multi-resident environment.
(3) We identify the research gaps and potential future directions for DFI localization and tracking.

The rest of the article is organized as follows. In Section 2, we introduce the fundamentals of device-free indoor localization and tracking. In Section 3, we review the technologies that can support localization and tracking in a multi-resident setting. Section 4 discusses the localization and tracking techniques for a multi-occupancy setting. Section 5 discusses the performance metrics. In Section 6, we discuss the open challenges and highlight the direction of future research. Finally, we conclude this article in Section 7.

2 AN OVERVIEW OF DEVICE-FREE INDOOR MULTI-RESIDENT LOCALIZATION AND TRACKING

In this section, we first introduce the concept of device-free indoor localization and tracking and the challenges related to its application in the multi-resident environment and then we present a taxonomy for device-free indoor location and tracking.

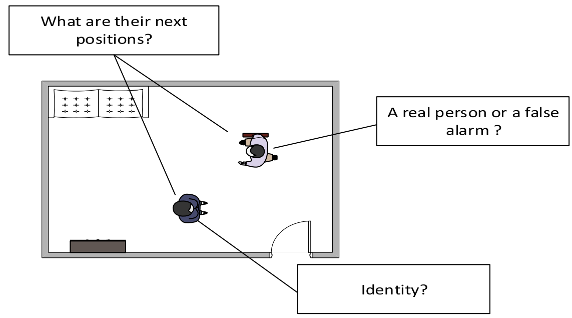

Fig. 1. Device-free indoor localization and tracking for multi-resident.

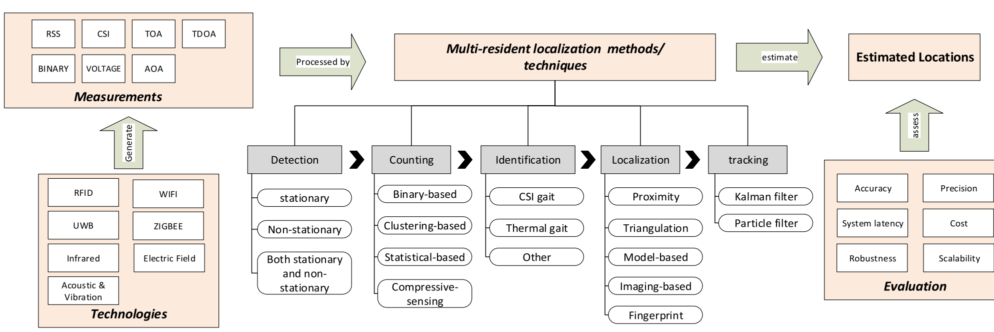

Fig. 2. Technologies and techniques for multi-resident localization and tracking.

Some pioneer works, such as References [12], [22], and [9], have demonstrated the feasibility of non-camera-based indoor localization and tracking that does not require the occupants to carry tracking devices. Reseach in DFI localization and tracking has accumulated much interest in recent years. Since 2006, the number of yearly publications on this topic is steadily on the increase. Some early works focused on single-resident localization and tracking while recent works focued on the more realistic multi-resident scenarios. A multi-resident scenario introduces additional challenges to localization and tracking, as shown in Figure 1.

First, any person may enter a monitored area,[1] move to anywhere in this area, and leave the area at any time. As a result, multiple residents may trigger multiple sensors at the same time. Also, the coexistence of multiple residents in the same monitored area can produce several complex localization and tracking situations, such as one person walking away from a group and two persons walking toward and passing each other. Such concurrent events make accurate localization and tracking difficult. Second, *free-of-device* means the identity information of residents is not available, which makes it difficult to maintain the tracks of a specific resident.

A general solution/procedure for multi-resident localization and tracking is given in Figure 2, where various *technologies* and *techniques* are utilized, together with relevant *measurements* and *evaluation metrics*. Figure 2 also gives a classification of techniques. It is worth noting that the rest of this article is organized based on this procedure.

To preserve the privacy of persons, passive sensing technologies are adopted including Radio Frequency Identification (RFID) [23], Wi-Fi [24], UWB [25], Zigbee [9], infrared [26], electric fields [16], and acoustic and vibration [27]. These technologies produce a set of measurements as shown

[1]We call the person who enters a monitored area *resident*.

in Figure 2. The details of the measurements are not included here because they are well known and have been already discussed extensively. When deployed sensors detect changes in measurements caused by persons entering in a monitored area, the human detection step is performed to initiate localization and tracking. In this step, there are three classes for presence detection: *non-stationary, stationary,* and *both stationary and non-stationary*. Next, The number of persons is counted and maintained to ensure that there is no missing person. Human counting techniques are categorized into *binary-based, clustering-based, statistical-based,* and *compressive sensing-based counting*. Then, each person is identified and this information to keep track of each person. The types of identification approaches are classified as *CSI gait-based, Thermal gait-based,* and *other approaches.* Finally, the estimated locations of persons are determined by localization and tracking techniques. Localization techniques and tracking techniques can be applied together or interchangeably to estimate location of persons. The catergories of localization technique are *proximity, triangulation, model-based, imaging-based,* and *RF fingerprinting-based technique.* For tracking techniques, there are two groups of technique, including *kalman filter* and *particle filer.*

3 TECHNOLOGIES

In this section, we describe technologies that can be used for DFI localization and tracking. These technologies include *radio frequency, infrared, acoustic and vibration*, and *electric field.* We also compare them to gauge their capacity in supporting localization in the multi-resident setting.

3.1 Radio Frequency

Radio frequency [18] refers to the group of technologies that relies on radio waves or electromagnetic signals to transmit information. Radio frequency technologies that facilitate device-free indoor localization and tracking include RFID, Wi-Fi, Wireless sensor network, and UWB.

3.1.1 Radio Frequency Identification. RFID is a type of radio frequency technology that uses RF-compatible integrated circuits to store and retrieve data sent through electromagnetic transmission [18]. The core elements of an RFID system include an *RFID reader* and *RFID tags.* There are two types of RFID tags: *passive* and *active*. Passive tags are generally cheap and small and require no battery. Active tags need batteries but have better coverage than passive ones.

In the literature, Liu et al. [28] proposed a fault-tolerant sequential pattern mining to extract frequency patterns from noisy data generated from an array of RFID tags. Ruan et al. [29, 30] attached several passive RFID tags on the wall and divided monitor areas to small grids with each grid representing a user location. Ma et al. [31] deployed two arrays of RFID tags orthogonally on walls to locate the x- and y-axes of the target's location separately and then applied particle swarm optimization (PSO) to localize the target.

3.1.2 Wi-Fi. Wi-Fi is a mid-range RF technology that is commonly used to create a local area network [18]. Nowadays many buildings are installed with Wi-Fi infrastructure, which makes it possible to use existing infrastructure for localization and tracking. Moussa and Youssef [32] was the first to employ Wi-Fi technology and utilize a received signal strength (RSS) measurement to realize device-free localization. Unlike RSS, which can only give an average value of the signal strength over an entire channel, channel state information (CSI) can provide detailed information of communication links. Thus, it is promising to use CSI measurements to localize multiple targets. Wang et al. [33] used the CSI measurement to estimate fine-grained locations of multiple sparsely located persons. Adib and Katabi [34] described how Wi-Fi signals reflecting off moving persons can be extracted to enable through-the-wall tracking.

3.1.3 Zigbee/IEEE 802.15.4. Zigbee/IEEE 802.15.4 is a low-data-rate, low-power communication protocol, which is suitable for creating wireless person area network for localizing and tracking a single or multiple persons in the long run [17]. MICA2 sensor nodes were used by Zhang et al. [9] to form a grid sensor array. RASS was introduced by Zhang et al. [35] to divide a large area to small triangle cells with each of the cell formed by three TalosB nodes. Both works allowed multiple targets to be detected when they are located in different grids. In addition, the grid size can be adjusted to improve the accuracy of both solution, but it may increase the cost of sensor deployment if the grid size is deceased Wilson and Patwari [36] proposed the radio tomography imaging (RTI) technique, which can detect and locate multiple persons in real time in an array of TelosB wireless nodes. While the above works required a dense deployment of the sensor nodes, Wang et al. [37] leveraged compressive sensing theory, which can reconstruct a signal from a few measurements to reduce the number of sensor nodes deployed on a monitored area. In this work, 24 MICAZ nodes were deployed to monitor an area of 144 m^2.

3.1.4 UWB. Ultra-wide bandwidth (UWB) is a promising technology for DFI localization and tracking, as it is not interfered with by conventional narrowband and carrier wave transmission in the same frequency band and can penetrate obstacles such as walls and furniture [38, 39]. In addition, the reflections from static objects in an environment and the reflections from a moving person can be distinguished due to the superior time resolution of UWB [40].

In the literature, Kilic et al. [25] conducted an empirical study of UWB signal for device-free indoor localization and proposed a method for single-person detection and distance estimation. Gulmezoglu et al. [40] proposed a UWB system that can detect and track up to two moving persons using four UWB sensors that measure the travel time of signals between UWB sensors and human subjects. Liang et al. [41] were able to detect and locate multiple stationary persons though a wall using a UWB radar system.

3.2 Infrared

Passive infrared sensor (PIR) detects heat radiated from a human body and uses it to localize and track a person [42, 43]. Qi et al. [44] developed two types of two-column infrared sensor modules with each column consisting of four infrared sensors using the Fresnel lens arrays. A type I module has three Fresnel lenses to form a field of view (FOV) in each infrared sensor for multiple targets tracking. The FOV in a type II module is modulated by pseudo-random coded masks, which allows various human motion attributes to be captured for target identification. Similarly, Yang et al. [45] developed a custom PIR node consisting of six sensors that are arranged to form 12 overlapped detection zones around a sensor node to track multiple persons. The purpose of the arrangement is to estimate the detection angle of each PIR node. The intersections of these detection angles can be used to determine the locations of multiple persons. Tao et al. [46] deployed an array of PIR sensors on the ceiling to avoid obstruction of sensors' FOV caused by furniture. Each PIR sensors has no overlapping with adjacent PIR sensors to reduce ambiguity and improve the tracking accuracy of multiple persons.

3.3 Acoustics and Vibration

Acoustic devices such as microphones can be used for estimating locations of persons [19]. In general, a set of microphones is used to measure the time that sound or vibration travels through a medium from a target to these devices. TDOA can be used to determine the location of persons. Hnat et al. [15] presented the Doorjamb system, which uses an ultrasonic device to detect the presence of a person as well as to measure the height of a person. It can track and estimate which

Table 1. Advantages and Disadvantages of Each Localization and Tracking Technology

Technology	Advantages	Limitations
RFID	–low cost, low power	–low coverage distance –signal collision –active tag and reader is expensive
Wi-Fi	–wide coverage distance –existing Wi-Fi infrastructure can be utilized	–high energy consumption
Zigbee	–low power consumption –low cost	– vulnerable to interference –short coverage distance
UWB	–high accuracy –good penetration –less interfere	– high cost –interference by metallic material
Infrared	–low cost, simple –low power	–limited coverage distance –false detection due to background temperature –low sensitivity to fine motion
Acoustic	–good accuracy	–susceptible to background noise –affected by multiple sources
Electric field	–high accuracy –low power, low cost (passive electric field)	–difficult to deploy –low coverage distance –susceptible to electromagnetic interference

rooms are occupied and who are in these rooms. Chen et al. [27] captured seismic signals that are caused by footsteps to locate a person using three geophones.

3.4 Electric Field

DFI localization and tracking in this area relys on changes in capacitive coupling on an electric field that is induced by a person entering a monitored area. Braun et al. [47] and Valtonen et al. [3] deployed capacitive floor mats in their testbeds. Pressure from a footstep of an occupant causes a capacity change in the sensors. Thus, the location of a person can be determined. Fu et al. [48] used the capacitive floor mats but actual electric potential sensors were installed on a side of a monitor area for ease of maintenance. While both works require a person to interact with the sensors directly, Grosse-Puppendahl et al. [16] proposed to use an electric potential sensor to detect electric potential changes in an environment caused by a human body.

3.5 Comparison between Device-free Technologies

The technologies for DFI localization and tracking have their strengths and weaknesses. A summary of the advantages and limitations of different technologies is presented in Table 1.

The main advantage of RF-based technologies over other non-RF technologies, such as infrared, is that they are able to penetrate obstacle such as walls, doors, and so on. Thus, it is quite appropriate to apply in indoor areas that are cluttered with walls, doors, and furniture, such as residential homes and offices. RFID technology is quite cheap and has low power consumption, especially passive RFID tags, but active RFID tags and RFID readers can be quite costly [18]. To cover a large area such as a hall, a warehouse, a large number of RFID tags must be deployed, because RFID has a short coverage distance [19]. This can incur high deployment cost. Moreover, reading multiple tags at the same time can lead to signal collisions. The loss of data caused by the collision can affect localization and tracking accuracy. Wi-Fi technology can cover a long distance, which makes it a good candidate for localization in a large-scale area. Implementing a Wi-Fi-based localization system can be fast and cheap, because we can utilize an existing Wi-Fi infrastructure in a building. However, Wi-Fi-based devices such as routers and access points require constant energy to maintain their operation and coverage. This need results in high energy consumption. Unlike Wi-Fi, Zigbee consumes less energy at the cost of a limited coverage distance. Although Zigbee-based transceivers and receivers are quite cheap, a dense deployment of transceivers and receivers can significantly increase the cost of the localization and tracking system. Compared to RFID, Wi-Fi, and Zigbee, UWB is less susceptible to interference of other signals and has good penetration. Thus, it achieves high accuracy in localization and tracking but may be quite expensive [39].

For non-RF technology, infrared provides a cheap, simple, and energy-efficient solution for localization and tracking [12, 13]. However, it has a limited range, which makes it less appropriate for a large-scale area [9]. Other drawbacks are that a false detection can often occur due to background temperature and fine motion is difficult to detect using infrared technology. An acoustic-based system can achieve good accuracy, but background noise and multiple sources of sound and vibration can considerably affect its accuracy [49]. An electric field can provide an accurate localization result due to a dense deployment of electric field sensors. However, the deployment process can be difficult and costly, because the sensors usually are placed on a floor, and furniture needs to be relocated during the installation [3, 47, 48]. In addition, electromagnetic interference can affect its accuracy [16].

4 TECHNIQUES

In this section, we discuss the techniques for implementing DFI localization and tracking. First, we discuss the human detection techniques in Section 4.1. The techniques for human counting are presented in Section 4.2. The techniques for human identification are presented in Section 4.3, and the indoor localization and tracking techniques are discussed in Sections 4.4 and 4.5, respectively.

4.1 Human Detection

To track a person, the first task is to detect the presence of a person. When a person enters a monitored area, this person's body interferes with signals transmitted from sensors, and we can analyse sensor readings to infer such an event. Mainly there are three classes for presence detection: *non-stationary, stationary*, and *both stationary and non-stationary* human detection.

4.1.1 Non-stationary Human Detection. This type of detection aims to detect a person from his or her movements. In general, measurements are stable in a monitored area without any person present. When persons enter into or move in a monitored area, the movements cause changes in measurements. Thus, the difference of measurements between with and without movements can be used to determine the presence of persons.

Zappi et al. [50] deployed three PIR sensors in three different orientations allowing the detection of multiple targets walking side by side in a small hallway. In References [51] and [52], the authors not only detected the presence of persons and their directions but also estimated their coarse locations. However, an increase in the number of persons affected the detection accuracy. Zou et al. [53] used two commodity Wi-Fi routers to detect a person moving past these routers by comparing the similarity between static CSI and occupied CSI measurements in the time domain. Compared to infrared and ultrasonic, Wi-Fi can provide better coverage and is suitable for a large hallway or entrance.

The detection at a hallway or entrance may be suitable for certain types of areas that only entrance and exit information are needed, such as museums and libraries. But it may not be suitable for an office or home that detection must be performed for an entire area. Moussa and Youssef [32] proposed an RSS fingerprinting technique that compares measurements collected during the offline phase to current measurements in the online phase as the alternative to their previous threshold-based methods [22]. RSS fingerprinting may not perform well in the real-world environment, as changes in the environment can affect the detection accuracy. Kosba et al. [54] addressed this problem by updating the offline fingerprints according to changes in the environment. Thus, this work is more robust and accurate than the previous one. Zhang et al. [9] modelled RSS changing behaviours in WSNs consisting of Zigbee-based sensors to detect the movement of a person. However, detection latency increases with node density. RASS [35] adopted the same model while utilizing multi-communication channels and proposed triangle topology for a sensor deployment to reduce the latency significantly. Because RSS measurements are susceptible to severe multipath effects in an indoor environment, Xiao et al. [55] leveraged CSI measurement of Wi-Fi devices, which is more stable as a fingerprint, as it detected the shift of CSI feature patterns to indicate the presence of a moving person in the monitored area. Similarly, Xiao et al. [56] used burst patterns in CSI amplitude measurement to detect a moving person but their detection method was based on a threshold value. Gong et al. [57] proposed an adaptive scheme that can automatically adjust threshold values according to multipath propagation in different monitored areas. Thus, this approach can facilitate threshold calibration of CSI measurement. Instead of using the CSI amplitude as the above Wi-Fi works, Xin et al. [58] detected a moving person based on the phase difference of CSI amplitude in multiple receiving antennas, but a slow-moving person was difficult to detect as the difference could be too small. The above works based on CSI amplitude could detect a fast-moving person accurately, but they failed to detect a slow-moving person. Compared to CSI amplitude, CSI phase is more sensitive to slow movements of a person. Thus, both the amplitude and phase of CSI measurement were employed in References [59] and [60] to detect a person with fast movement and slow movement.

4.1.2 Stationary Human Detection. Compared to non-stationary detection, stationary human detection is challenging, as a stationary person induces only small changes or does not produce any change in measurements at all [61, 62]. It is almost impossible to detect a stationary person with PIR technology, because PIR technology relies on movements of a person to cause the temperature difference in an environment [63]. However, RF technologies such as UWB and Wi-Fi are promising, as they are sensitive to any changes in a monitored area.

The influence of a human presence on RF links, such as shadowing and reflection, can be used to detect a stationary person. Palipana et al. [64] modelled non-linearities in CSI amplitude under the influence of a person and used it to detect a static person. However, they could only accurately detect a person standing in a line of sight between a transceiver and receiver. Omnidirectional Passive Human Detection (Omni-PHD) was introduced in References [65] and [66] to detect a human in four directions. Kilic et al. [38] relied on the delay of reflected signals to determine a presence of a person in a UWB network. Yuan et al. [61] employed a variance of time of flight (TOF) to detect a static person through a wall.

To detect a stationary person, vital signs of a human such as breathing can be used as an intrinsic indicator. An early work could detect a person by capturing chest motions caused by breathing, but it utilized an expensive radar infrastructure [67]. Alternatively, Patwari et al. [68] detected a breathing person using sinusoidal variation in RSS measurements, but it required a dense sensor deployment. Kaltiokallio et al. [69] utilized only a pair of TX and RX to determine the presence of a person but required a dedicated setup. Wi-Fi hardware was also employed to detect a person from his or her breathing. Using a similar setup as in Reference [69], Liu et al. [70] could detect a person breathing using CSI measurements. While the above works detected the presence of a person in a very small area, Wu et al. [71] could detect a person from his or her breathing in a much larger area using some Wi-Fi routers. UWB technology can also be used to detect a station person from vital signs. Liang and Deng [72] extracted a vital jiggle signal, i.e., chest or heart movement, from a transmitted signal between the UWB radar and a person to detect a person through a wall. Liang et al. [41] utilized multiple-input and multiple-output (MIMO) UWB radar to detect multiple stationary persons through the wall simultaneously.

4.3.3 Both Stationary and Non-stationary Target Detection. In some application such as remote health monitoring and intrusion detection, a person may or may not move but it is required to continually detect the person. Therefore, we are required to detect both moving and stationary person.

Braun et al. [47] were able to detect both stationary and moving-person using capacitive floor mats but the deployment of the floor mats may not be practical if a room was already occupied by furniture. Zhao et al. [62] used the histogram difference of RSS measurements to detect both stationary and moving persons, but it required a dense deployment of RF nodes. Zhou et al. [73] leveraged CSI fingerprint and support vector machine (SVM) to detect a person regardless of his or her motion state. Han et al. [74] constructed a frequency-based fingerprint from CSI measurement. In addition to the detection of a person, the state of a person, i.e., stationary or moving, can be distinguished. Fang et al. [75] employed a deep learning approach that analysed both CSI amplitude and phase information to detect the presence of a person as well as his or her basic activities such as walking and sleeping.

Domenico et al. [76] used features of the mean Doppler spectrum estimated from CSI measurements to enable through-the-wall presence detection for both stationary and moving persons. The above works offer an end-to-end process to detect both moving and stationary person. The following works require two separate methods to detect a moving and stationary person. Wu et al. [71] employed both CSI amplitude and phase information to enable the detection of a moving person with dynamic speed and the detection of a stationary person through breathing. Adib et al. [77] adopted frequency modulated carrier waves (FMCW) to detect a moving person using the changes in time of flight (ToF). To overcome the issue that a stationary person could not be detected because of the elimination of reflections of all static objects, including a stationary person, the authors also use breathing as an indicator for detecting stationary persons.

4.2 Human Counting

Target counting can be used for a wide range of applications. For example, energy consumption can be managed efficiently if we can accurately count the number of persons in an indoor area such as home and office. The counting techniques can be classified into *binary-based, clustering-based, statistical-based*, and *compressive sensing-based* counting.

4.2.1 Binary-based Techniques. In this technique, binary sensors such as PIR sensor are installed in a monitored area. A sensor generates an output of "1" if one or more persons stay within its detection area. Otherwise, a "0" is generated when no one is in the area. Based on this fact, snapshot-based counting has been employed to count the number of persons in References [78–80]. The snapshot technique considers states of all binary sensors, i.e., on or off, at a particular time as a snapshot and use this information to count the number of people. Song and Wang [79] proposed a dynamic colouring technique (DEC) to estimate the number of persons by creating and maintaining a set of target distribution scenarios of different colours. For each scenario, shrinking and expanding methods were introduced to determine feasible regions of persons based on sensor reading before and after an event. This work was further improved in Reference [78]: Instead of utilizing only a single snapshot, a sequence of snapshots that contains both spatial and temporal dependencies was used to improve the estimation accuracy. Wahl et al. [81, 82] relied on occupants' paths extracted from PIR sensors that are distributed systematically in an office area to count the number of persons and require fewer sensors than the above works. Due to the binary measurement, the technique is not computationally expensive, but false detections, which often occur for binary sensors, can degrede the accuracy of the person count.

4.2.2 Clustering-based Techniques. Clustering-based techniques are focused on identifying multiple non-overlapping clusters, each of which may contain one or more targets. The objective is to cluster measurements generated by different persons so the number of clusters can infer the number of persons in a monitor area. Zhang and Ni [83] deployed a grid of wireless nodes on the ceiling to monitor persons passively. In the multiple person setting, clusters of communication links are formed according to the number of persons. However, it can only provide accurate counting when a person is not close to each other. ACE [84] employed hierarchical agglomerative clustering to group candidate locations and counting the number of persons without any prior knowledge of the number of persons. Similarly, attenuation peaks occurring in RF imaging–based localization or radio tomographic imaging (RTI) localization can be counted to indicate the number of persons [85]. However, it may not be accurate as some peaks may be noise. Thus, clustering techniques were also employed to remove noise and improve the accuracy of the counting. Nannuru et al. [86] employed *k*-means clustering to track the number of persons in their RTI system, because the number of persons is known in advance. Wang et al. [85] employed soft clustering techniques to determine the number of persons without prior knowledge. Similarily, Zamzami et al. [87] used soft clustering to group data generated from different types of sensors, e.g., PIR, temperature, and humidity, to estimate the number of occupants. However, the clustering approach may provide inaccurate counting, because two persons staying close to each other may result in only one cluster due to similarity of measurements.

4.2.3 Statistical-based Techniques. Statistical-based techniques rely on statistical models to estimate the number of persons. The probability distribution function can be used to represent the distribution of multiple persons. Raykov et al. [88] used a single analogue PIR sensor to count the number of persons and modelled the PIR data from different meetings with different Laplace distributions. Then, regression techniques are employed to determine the number of occupants. Wu et al. [89] represented a distribution of multiple persons in a wireless sensor network using a specific probability distribution that can be estimated using the regression techniques. Then, the number of persons is estimated by a maximum likelihood estimation technique. Depatla et al. [90] modelled the probability distribution of the received signal amplitude as a function of the total number of occupants. Then, it was compared to the one obtained from experiments using the Kullback-Leibler divergence as a metric that shows how much two probability distributions differ from one another. Then, the argument that minimizes this metric is taken as the estimated number of occupants. Statistical metrics such as mean, variance, and so on, are also adopted in a number of works for occupancy estimation. Adib and Katabi [34] used spatial variance to indicate the number of persons. Thus, the spatial variance increases correspond to the number of persons. Domenico et al. [91] used mean and variance of CSI measurements as features for the linear discriminant classifier to estimate the number of targets. Xi et al. [92] formulated a stable monotonic function that describes the relationship between the number of occupants and variance-based CSI features. Then, a new metric based on the percentage of nonzero elements in a dilated CSI matrix was proposed to improve the accuracy of the occupancy counting.

4.2.4 Compressive-sensing-based Counting. In the compressive sensing (CS) theory, a monitored area is divided into N grids, which are represented as a signal vector of N elements and the number of persons in the monitored area is equal to K. The corresponding nth element of the signal vector is marked as "1" if there is a person in the nth grid and "0" otherwise. The number of persons is usually smaller than the number of grids, which indicates that the signal vector has a sparse nature. Thus, we can estimate the number of persons by recovering the signal vector from a vector of length M containing a small number of measurements instead of using measurements from all N grids. To be specific, given the measurement vector and a sensing matrix phase, which is obtained at the offline phase and contains the difference of measurement caused by a person for each of the N grids, a signal vector with a minimum possible number of nonzero entries can be computed. The advantages of CS theory is that the estimation of a location and the number of persons is in general accurate. However, this technique also suffers from the complexity of sparse signal recovery.

Zhang et al. [93] was the first to prove the applicability of CS theory for the counting problem and proposed a variant of the matching pursuit algorithm, so-called greedy matching pursuit, which does not require prior knowledge such as the number of persons and was more efficient than other approaches such as orthogonal matching pursuit (OMP) and sparsity adaptive matching pursuit (SAMP). Wang et al. [37] applied the same algorithm to solve the problem of counting and localizing persons in a large-scale area and proposed a systematic approach to select an appropriate grid size to achieve higher accuracy. Wang et al. [94] proposed the E-HIPA system, which leverages the advantage of CS theory to reduce the number of sensor nodes. Thus, their work is energy efficient. In addition, the proposed adaptive orthogonal matching pursuit (AOMP) algorithm is more efficient than OMP and SAMP. The above works assume that a person stays inside a grid only. Therefore, a sparsifying dictionary can be constructed corresponding to the grid and the representation coefficient encrypts the number and positions of multiple persons. However, the violation of this assumption can affect the accuracy of compressive sensing due to the dictionary mismatch between the assumed and actual ones. Sun et al. [95] dynamically adjust the grid to alleviate or even eliminate dictionary mismatch. Guo et al. [96] proposed a more accurate sparse approximation model to reduce errors created by off-grid and incorporated incomplete prior information to improve the counting and localization accuracy for off-grid persons. Both off-grid works achieved a higher accuracy, but their complexity is signification higher due to their iterative algorithm compared to the on-grid ones.

4.3 Human Identification

Target identification is one of the important tasks for localization and tracking of multiple persons as it allows us to distinguish between different persons correctly, which improves the accuracy of localization and tracking. We categorize approaches for target identification based on types of collected data or signal. As a result, there are three categories including *CSI gait-based, Thermal gait-based*, and *other approaches.*

4.3.1 CSI gait-based Target Identification. Channel state information of Wi-Fi devices contains useful information and can be used to identify a person. The CSI gait approaches focus on extracting a step cycle of a person and use this information to identify a person. Zeng et al. [97] was the first work that realized person identification using wireless signals. To identify a person, step cycle and walking behaviours were extracted from CSI amplitude using a peak–valley detection algorithm and frequency domain analysis, respectively. Similarly, Zhang et al. [98] employed CSI amplitude but extracted only walking behaviour from the CSI data. Instead of CSI amplitude, Hong et al. [99] used subcarrier–amplitude frequency (SAF), which is the frequency on values of each subcarrier and amplitude pair, as a feature and achieved a better result than in References [97] and [98]. In References [100] and [101], CSI data were divided into segments according to walking steps. Thus, per-step features can be extracted and utilized together with walking behaviours to improve identification accuracy as well as to recognize strangers. Although these works can achieve a good identification result, they perform identification for the single-person setting only. In addition, persons need to walk in a straight line without stopping or changing direction; otherwise, the identification may fail.

4.3.2 Thermal Gait-based Target Identification. Infrared light emitted from human bodies can be detected by a PIR sensor equipped with a Fresnel lens. The lens divides a detection area of a PIR sensor into different zones. Thus, body parts of a person generating distinct sensor readings can be used to identify this person. Qi et al. [44] developed a double-column sensor module that each column has four binary PIR sensors with FOV masking and also proposed a fusion scheme to improve the identification accuracy, especially for a single person. An analogue output of the PIR sensor was later employed, as it provides more features than the binary one. Yun and Lee [102] utilized time-domain features such as amplitude and passage duration as a person's profile and used SVM to achieve a promising result. While the previously mentioned works utilized only features from the time domain, Xiong et al. [103] extracted features for both time and frequency domain. Thus, they can achieve better results for multiple moving persons. Xiong et al. [104] utilized frequency domain features extracted by Fourier transform, short-time Fourier transform, and wavelet packet transform and fused them to identify a person walking past an array of different height PIR sensors. This work provided a good identification result as each part of a human body was captured by individual sensors. Yan et al. [105] conducted an empirical study on the factors that affect human identification using PIR sensors; then, a mathematical model is derived to map the relationship between two factors and their influence on identification accuracy. One challenge of the thermal gait approach is that hardware cost can be high, because it relies on a large number of PIR sensors to capture different parts of a human body. Changes in ambient temperature or person clothing can also affect the identification performance. These issues may prohibit the use of this approach in real-life conditions.

4.3.2 Other Approaches. Instead of utilizing gait information, some existing works rely on other types of information to identify a person. Tao et al. [46] distinguished each person based on object interaction and behaviours such as private desk information, room entering/leaving information, path, and speed. Hsu et al. [106] leveraged RF reflections to capture users–object interactions as an image. Then, the convolution neural network (CNN) was adopted to identify persons. However, these works rely heavily on prior knowledge such as object locations and map layout. Alterations of this information can affect the identification rate considerably. The physical properties of a person can also be used to diffferentiate between persons. Hnat et al. [15] measured the height of a person using ultrasonic sensors and used this information to identify a person. However, identifying persons with the same height is an issue in this work. Zhao et al. [107] leveraged millimeter wave radar to capture the body shape of each person and used this information sequentially so both body shape information and movement behaviours were taken into account.

4.4 Localization

In this section, we describe the fundamental techniques for indoor localization including *proximity, triangulation, model-based, imaging-based,* and *RF fingerprinting-based* techniques.

4.4.1 Proximity-based Localization. Proximity techniques provide symbolic relative location information. Usually, it relies upon a dense grid of sensor nodes, each having a well-known position. When a single sensor node detects a person, the person is considered to be co-located with it, as

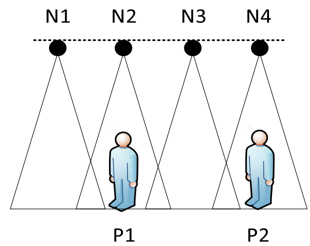

Fig. 3. Illustration of proximity-based techniques.

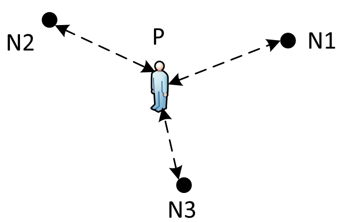

Fig. 4. localization based on lateration techniques.

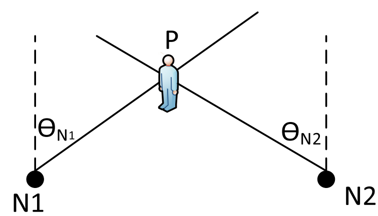

Fig. 5. localization based on angulation techniques.

shown in Figure 3. For example, the person P1 activates the sensor node N2. Thus, the location of the person P1 is considered to be the same as the location of a sensor node N2. This method is in general easy to implement using different types of technologies. In particular, device-free indoor localization systems using infrared [108] and RFID [109] are often based on this method. If a person i is in the range of sensor j, then the measurement is equal to "1"; otherwise, it is equal to "0." A threshold value is used to determine whether a person is in range or out of range.

Hosokawa et al. [110] relied on an array of PIR sensors attached on the ceiling to achieve accurate results. These works relied on the assumption that persons are likely to maintain their trajectories and desks information to solve the ambiguity caused by multiple people. Zhang et al. [109] used RFID tags array having passive tags and active tags to locate multiple persons as well as to determine their frequency trajectories. However, this approach relied on the assumption that persons do not change their direction abruptly and do not stand still. Similarly, Liu et al. [28] aimed to determine the frequency trajectories of persons from an array of active RFID while the deployment cost can be expensive due to the use of active RFID tags. Overall, the proximity technique is easy to implement while the localization result is coarse. This technique is suitable for applications that do not need high localization accuracy. To achieve a accurate result, high density of sensor nodes is required, which might not be practical and economical in a real-life situation.

4.4.2 Triangulation. A person's location can be estimated using the geometric properties of a triangle in the triangulation-based techniques. There are two categories: *lateration* and *angulation.*

As shown in Figure 4, in the lateration technique, a person P is located between the reference points N1, N2, and N3. For each reference point, we need to estimate the distance of the person and a reference point. Once the distances between the person and the three reference points are known, we can estimate the location of person P. Common measurements for lateration are time of arrival (TOA) and time difference of arrival (TDOA). The distance can be obtained by multiplying a radio signal velocity and travel time or by calculating the attenuation of radio signal strength [18]. Angulation (AOA estimation) techniques draw direction lines by measuring an angle of arrival (AOA) from each node to a person. Then, the intersection of several pairs of direction lines can be

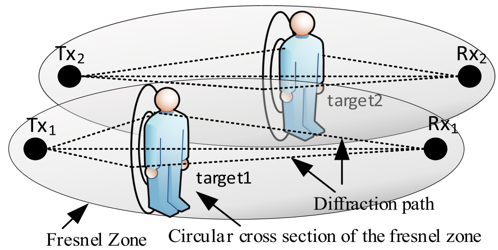

Fig. 6. Illustration of a Fresnel zone concept to model the effect of human locating between transceiver and receiver.

used to estimate the location of a person [111]. In Figure 5, two angles Θ_{N1} and Θ_{N1} are measured to identify the direction of the person P from nodes N1 and N2, respectively. Then, the two lines are drawn from two nodes. The intersection of the two lines is considered to be the location of person P.

The AOA technique is not computational expensive, as it only needs a weighted least squares linear system solver [112]. Wang et al. [113] leveraged multipath problem to measure AOA and this information to localize a person. Li et al. [114] used Dynamic Music algorithm to identify AOA of a signal from a moving person. Adib and Katabi [34] proposed the through-wall localization technique that extracts AOA of the RF signals reflected from a moving person to localize a person from static objects such as furniture and wall. One of the limitations of these two works is that they cannot detect the non-moving person. For TOA-based solutions, Adib et al. [77] relied on multi-shift FMCW to extract reflections from multiple persons. However, it required non-standard hardware. In addition, a coverage range is restricted to 10 m. Thus, it may not be suitable for large-scale deployment. Triangulation techniques can achieve good accuracy, but indoor environments such as walls and furniture pose issues such as multipath, which can affect accuracy. In addition, some specific hardware may be required to overcome the negative effects of indoor environments.

4.3.1 Model-based Localization. Model-based localization techniques can reduce or even avoid offline training efforts. A presence of a person in the Fresnel zone can affect transmitted signals such as absorption, diffraction, and reflection. For example, as shown in Figure 6, transmitted signals from a TX node can travel to an RX node through the lateral side of a person body due to the diffraction. Thus, there are diffraction paths. Provided that the distances from the diffraction points to the main link are known, the distance from a diffraction point of each path to a sensor can be estimated. Hence, we can model these effects mathematically and use them to determine the location of a person between TX and RX.

Shadowing models aim to characterize RF attenuation happens when a person obstructs RF links in a monitored area. There are different shadowing models. An excess path delay model proposed in References [23, 115] characterizes the influence of a human presence on communication between an RFID reader and passive RFID tags. Then, maximum likelihood and linear least squares methods were used to localize a person. Based on the same model, particle filtering and Kalman filtering are employed to locate a person [10]. An elliptical model can describe the RSS variation caused by a person obstruct a radio link. In this model, the RSS variation of RF links is inversely proportional to the square root of the length of the radio link. This model has been used in a number of papers such as References [37] and [116]. Instead of RSS variation, Wang et al. [117] proposed a shadowing model based on differential RSS that does not require a reference measurement to be collected and is more stable in a dynamic environment. While other models focused only on RF attenuation, the exponential-Rayleigh model (ERM) [118] not only considered

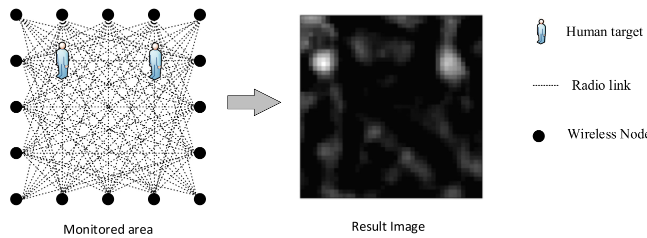

Fig. 7. Illustration of radio tomography image.

RF attenuation but also took the target-induced multipath interference in account. Thus, the accuracy of localization was improved. Compared to ERM, a saddle surface model (SaS) [119] took the distance to the transmitter and receiver in consideration. Hence, it could better describe the nature of the shadowing effect. In diffraction models, RF signals cannot penetrate a human body but are diffracted by the sides of a human body to travel to a receiver. Wang et al. [120] modelled a person as a cylinder and employed diffraction theory to characterise RSS changes accurately. This model has been employed in References [121, 122] and [123]. While other works focused on a RSS-based model, a power fading model [33] is used to describe the effect of human on a CSI measurement. Propagation fading, diffraction fading, and person absorption can influence the power fading between a transceiver and receiver. Then, a gradient descent (GD) and genetic algorithms are employed to estimate locations of persons. Although this appraoch can reduce the burden of fingerprint collection, model parameters need to be tuned for every new location.

4.4.4 Imaging-based Localization. Radio tomography imaging is a transmission-based imaging technique that relies on the signal strength from various links. The RTI system is centred on estimating an image vector that characterizes the amount of the signal attenuation caused by an object in a monitored area. Thus, the location of a person can be estimated as a location of the occurred attenuation in the monitored area as shown in Figure 7.

The RTI technique was first proposed by Wilson and Patwari [36]. It has been employed in many works, such as in References [124] and [117]. The RTI technique was further improved to provide a through-the-wall localization. The motion-induced variance of received signal strength was exploited to locate a moving person behind a wall in Reference [125]. However, locating stationary persons cannot be performed properly, because signal variation slowly diminishes, resulting in persons varnishing from the image. Kaltiokallio et al. [126] employed the fade level, which is a function of RSS to determine an RF link quality, and was able to locate a stationary person behind a wall. In Reference [127], the inverse area elliptical model (IAEM) was proposed to enable the RTI technique for a complex structured building. Multiple persons can be simultaneously detected in the RTI network due to high density of RF node. Based on the fact, a number of works were proposed to handle multiple persons: Nannuru et al. [86] proposed a magnitude model to localize up to three persons. However, the number of persons is fixed and a particle-based approach can incur high computational usage when the number of persons is increased. Bocca et al. [128] employed the fade level and adopted machine vision methods to detect up to four targets in real time. In addition, intersecting trajectories were handled in this work. Compared to the above works, Wang et al. [85] proposed variational a Bayesian Gaussian mixture model (VB-GMM) algorithm to locate multiple persons accurately without any knowledge of locations and the number of people. However, the RTI technique was quite computationally expensive, incurs high deployment cost, and creates high power consumption due to a high density of RF sensors. Some works focused on reducing the computational expense, such as in References [129] and [130]. To reduce the number

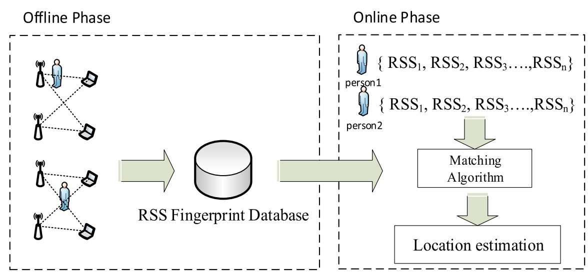

Fig. 8. Illustration of fingerprinting localization techniques.

of RF nodes, there was an attempt to incorporate the compressive sensing theory into the RTI framework including References [131–133].

4.4.5 RF Fingerprinting-based Localization. RF fingerprinting-based localization is a technique for estimating the location of a person by mapping the current measurements with the pre-collected fingerprints as shown in Figure 8. In general, it consists of two phases: the offline phase and the online phase [134]. In the offline phase, radio signals are observed when a person is at a known position in a target environment. Then, the observed signals are collected as fingerprint databases. In the online phase, the current radio signal at an unknown location is compared with those stored in the databases, and the closest match is returned as the estimated user location.

There are fingerprint-based localization techniques such as probabilistic methods [55, 135, 136], SVM [73], and neural networks [24, 137]. For RSS-based fingerprint, Seifeldin et al. [135] developed a Nuzzer system in a large-scale indoor setting with existing Wi-Fi infrastructure. However, localizing multiple persons can be difficult for Nuzzer. Xu et al. [138] localized multiple persons using a fingerprint collected from a single person. Thus, this can considerably reduce time and effort in fingerprint collection. Sabek et al. [84] used a cross-calibration technique and an energy minimization framework to reduce the calibration effort in the offline phase. In addition, the clustering technique was used to remove outliers and achieved better localization accuracy in multiple-person settings than Nuzzer and SCPL. Ruan et al. [29] leveraged human–object interaction to improve the localization accuracy of the fingerprint method. CSI-based fingerprinting exploits the amplitude and/or phase of each subcarrier of the channel. Thus, CSI fingerprinting is more robust and more accurate than the RSS one. Pilot [55] was the first to employ CSI measurement and proved that CSI is more superior that RSS. Then, CSI-based fingerprint localization became popular and has been adopted by many recent papers such as in References [139] and [73]. Due to rich features of CSI measurement, CSI-based fingerprint location not only can locate a person but also can estimate a person's basic activities or poses such as standing, walking, and squatting. Wang et al. [139] employed wavelet features that are more informative than both time and frequency domain features to perform localization and activity recognition simultaneously, but the suitable features must be manually explored and tested. As a result, it becomes labour intensive and time-consuming. However, this problem was addressed by a deep learning approach that can automatically extract and learn discriminative features [24]. To summarize, the collection of a fingerprint database is the main issue for this approach, especially a large-scale area, because it requires a long time and intense human efforts. The fingerprint collection can be alleviated by crowdsourcing in the device-based localization, but it is not possible in device-free settings. Some effort has been made to transfer a fingerprint from one location to another location [140]. Nevertheless, the trasferring methods can reduce the efforts to some extent and cannot obtain accurate results.

4.5 Tracking

In this section, we review the tracking techniques that are commonly used in indoor environments. There are two main categories of tracking techniques: Kalman filtering and particle filtering. In the rest of this section, we present the foundation of these two techniques and how they are used for multi-resident tracking in the existing solutions.

4.5.1 Kalman Filtering. Kalman filtering can use a set of noisy measurements observed over time to provide an accurate location estimation than a single measurement [141]. In general, Kalman technique assumes that a system model is linear and a posterior probability distribution is Gaussian. It has two phases that are performed recursively, including prediction and correction. The prediction phase predicts the state for the next time step. In the correction phase, the predicted state is corrected using the new measurement. The main advantages of Kalman filtering are that it is computationally efficient and relatively simple to implement [142]. For these reasons, the Kalman technique has been adopted by a number of papers to track a single person in the device-free localization and tracking system [10, 13, 125, 143]. In a multiple-person setting, the tracking problem can be complex nonlinear and non-Gaussian [117]. However, existing works have shown that Kalman filtering can handle this tracking problem [44, 128, 144, 145]. Essentially, they divided the multiple people tracking into a set of single-person tracking problems using data association methods. Then, each person is tracked using Kalman filtering independently. According to the above works, this is proof that Kalman filtering can provide an accurate location estimation for both single and multiple persons. However, these reviewed works assumed that a person movement is linear. Thus, a location estimation can be inaccurate when a person abruptly changes his or her walking speed or direction. Even though there are variations of Kalman filtering that can handle non-linear movements such as extended Kalman filter and unscented Kalman filter, most reviewed papers still prefer to use a traditional one due to its efficiency and accuracy.

4.5.2 Particle Filtering. Compared to linear problems, estimation of the posterior distribution of nonlinear problems is more difficult. Particle filtering uses a set of particles to represent the estimated posterior probability density. Thus, it is suitable for nonlinear systems and can handle very large stage space [141]. Similarly to Kalman filtering, it operates in two phases iteratively. In the prediction phase, particle filtering uses the principle of importance sampling to generate a set of samples. In the correction phase, weights of particles are assigned proportionally to the observation likelihood. However, particle filtering can suffer from a degeneracy problem whereby low-weighted particles are neglected or disappear after a few iterations [146]. As a result, particles lack diversity, so this problem decreases the performance of particle filtering dramatically. To overcome this issue, the effective sample size measurement and the resampling step are introduced to maintain the effective number of particles to maintain its accuracy. Many works have employed particle filtering successfully to track a single person, because it can handle non-linear motions accurately [119, 146, 147]. Thus, both stationary and moving persons can be tracked. Furthermore, many works also showed that particle filtering can track multiple persons, which is highly nonlinear [86, 118, 148, 149]. Despite its high accuracy in the location estimation, the efficiency of particle filtering depends on the number of particles and a dimension of a state. The particle filter can perform poorly for multiple-person tracking, which has a high state dimension and requires a large number of particles [142]. Although this problem can be addressed using one particle filter for each person [150], we should be careful when we applying the particle filter.

5 PERFORMANCE EVALUATION

In this section, we first describe the commonly used metrics for evaluating the performance of DFI localization and tracking systems, and then we compare some existing works based on these metrics. The metrics described in this section include: (1) accuracy, (2) precision, (3) real-time complexity, (4) cost, (5) bobustness, and (6) scalability.

5.1 Accuracy

Accuracy is a major concern for localization and tracking of multiple persons. In general, to measure accuracy, estimations are compared with ground truths. In our review, we discuss the accuracy for three tasks including localization, identification, and counting.

There are two widely used accuracy metrics for localization and tracking: the *mean distance error* and the *location error rate*. The former metric is used to measure the accuracy for a two-dimensional location. The mean distance error is calculated by averaging the Euclidean distance between the predicted coordinates and the ground-truth coordinates. The latter is mainly adopted for discrete location estimation. It is calculated by dividing the number of correct locations with a total number of locations. For target identification, the commonly used metric for evaluating target identification is identification rate, and it can be calculated by dividing the correction identification with the total number of ground truths. In addition, a confusion matrix can be used to analyse the identification results. To measure the accuracy of person counting, the estimated number of targets is compared to the actual number of targets. The accuracy of target counting then can be calculated using counting percentage, which is a ratio between the estimated count and the actual number of persons.

5.2 Precision

DFI localization and tracking systems not only need to provide location estimations accurately but also need to perform consistently, i.e., they need to produce less variation in their results over a series of trials. Precision is a metric that determines the consistency of location estimation. It is normally used in conjunction with accuracy. Cumulative probability functions (CDF) of a distance error can be used for measuring the precision of DFI localization and tracking systems. It gives the distance error between distributions of the estimated location and the actual location. For example, if the CDF of the first system is 90% within 2.3 m and the CDF of the second one is 50% within 2.3 m, then, it is favourable to select the first system, as it is more consistent than the second one.

5.3 System Latency

System latency measures how fast a DFI localization and tracking system processes measurements and locates a person in real time. Based on our review, most works report the system latency by measuring the total time that is required to compute estimations in units of seconds or milliseconds.

5.4 Cost

The cost can affect the adoption of a proposed solution. The cost usually comprises three parts: hardware cost, energy cost, and human effort cost. Ideal solutions should have reasonable hardware cost. In addition, the solutions should require fewer human efforts and time to install and calibrate. The power consumption of the solution should be low so that it can reduce energy cost. A cost-efficient solution can be achieved by analysing and understanding the needs of the localization and tracking system, e.g., area size, resolution of localization and tracking result, and the number of occupants.

5.5 Robustness

Robustness means a DFI localization and tracking system performs properly even when there are irregular or incomplete measurements caused by sensor breakdown, severe environment, or different deployment environments. Robustness can be evaluated by conducting experiments in testbeds that have various geographical layouts and furniture. For example, a large hall may experience a less multipath problem than a cluttered office room. Then, the accuracy of various testbeds is compared. Mean distance error and CDF of a distance error can be used as metrics in a comparison of these results. In addition, a sensitivity analysis, which evaluates each output to determine its contribution toward an output uncertainty, could be used to measure the robustness.

5.6 Scalability

Scalability means a system can scale to different size of areas. Scalability requires that the performance of a system should not decrease dramatically in a large deployment area. Normally, the scalability is evaluated in relation to the accuracy. Experiments in the reviewed papers are usually conducted on a few testbeds that have different area size. Then, the results of these experiments are compared to determine how accurate their systems are when the size of a monitor area is varied. The scalability can be determined in term of the density of sensor nodes. It refers to the number of sensor nodes per unit area, e.g., nodes per square meter. Scalability can be calculated using not only the density of sensor nodes but also the density of persons.

5.7 Performance Comparison

Based on the above-discussed metrics, we evaluate and compare some existing works for DFI localization and tracking as shown in Table 2. We have selected the state-of-the-art works by their respective technologies. We extracted the actual values from their works and then present them in the table.

From the table, we can see that Zigbee/IEEE 802.15.4 and Wi-Fi are adopted by a majority of the reviewed papers, including the ones shown in the table, due to their reasonable cost and availability as off-the-shelf products, whereas UWB is more expensive and less used. Other technologies, such as RFID and PIR, are also adopted for small-area settings due to their short coverage distance. RSS measurement is popular among RF technology as it is relatively easy to implement. Similarily, Triangulation-based measurements such as AOA and TOA are popular, as they can be measured using different technologies, whereas CSI measurement is limited to Wi-Fi technology only, and binary measurement is less popular, as the information it can provide is limited. The localization techniques such as fingerprint, model-based, and triangulation are applicable for most indoor localization and tracking scenario.Imaging-based techniques require specific setup, which is more appropriate for the through-the-wall scenario than general localization and tracking scenarios. The accuracy of these works is reasonable with respect to their techniques and settings. They can locate a person with an error of less than 1 m. The best result can be achieved with less than 20 cm error, but such approaches usually require the dense deployment of sensor nodes or specific equipment. Most works in the table can provide real-time localization and tracking with latency lower than 1 s. However, they only conducted experiments using a small number of people. It is questionable to see how well they can handle a large number of people.

The robustness of these systems is tested on different testbeds as shown in the robustness column in Table 2. Most of them can achieve 70–90% of the acceptable accuracy, but they only experiment in a controlled manner, which makes it hard to interpret their performance in a real-life situation. The scalability of each work is tested with the area size between 70 and 150 m^2. Only a few works in the table tackle a larger area, but we observe that all of them localize only a small number of persons, i.e., three to five persons. This indicates that the current state-of-the-art works are not tested in a large crowd setting. For the cost of deployment, Zigbee, RFID, and PIR use a similar number of sensors to cover a monitored area. However, Zigbee and RFID have the advantage of being RF technology and thus are more appropriate to deploy in a cluttered area than PIR.

Table 2. Comparison of Existing DFI Localization and Tracking Solutions

Technology	Measurement	Reference	Technique	Accuracy	Precision	Latency	Robustness	Scalability	Deployment Cost
Zigbee	RSS	[138]	FP	≈1.3 m	N/A	≈0.9 s	office open area	150 m^2, 400 m^2	22 sensors 20 sensors
	RSS	[128]	IM	≈0.45–0.55 m	80% less than 0.6m	≈0.015 s	open area apartment office	70 m^2 58 m^2 67 m^2	30 sensors 33 sensors 32 sensors
	RSS	[35]	MD	≈1 m	70% less than 1m	≈0.26 s	open area	400 m^2	23 sensors
	RSS	[151]	MD	≈0.8–1 m	80% less than 2m	≈2 s	open area	108 m^2 300 m^2	16 sensors 63 sensors
RFID	RSS	[109]	PX	99%–75%	N/A	≈30 s	open area	N/A	5 readers 81 tags
	RSS	[113]	TR	≈0.17 m	90% less than 0.17m	≈0.5 s	lab library open area	108 m^2 70 m^2 75 m^2	Each area 4 readers 21 tags
Wi-Fi	CSI	[33]	MD	≈0.5 m	80% less than 0.7m	≈0.065 s	home classroom library	150 m^2 70 m^2 108 m^2	Each area 4 aps 7 mps
	RSS	[84]	FP	≈1.3 m	80% less than 3m	≈0.002 s	apartment office	114 m^2 130 m^2	Each area 2 aps 3 mps
	RSS	[135]	FP	≈2 m	75% less than 9.3m	≈0.003 s	office	750 m^2 130 m^2	3 aps, 2 mps 3 aps, 3 mps
INFRARED	AOA	[149]	TR	≈0.5 m	N/A	≈19 s	open area	100 m^2	9 nodes
	BIN	[46]	PX	≈0.3–0.4 m	90% less than 2m	N/A	office	128 m^2	43 sensors
	AOA	[44]	TR	≈0.5 m	N/A	N/A	open area	81 m^2	4 nodes
UWB	AOA	[40]	TR	≈0.25m	N/A	≈1 s	office	9 m^2	4 sensors
	TOA	[38]	TR	≈0.12–1.8 m	N/A	N/A	open area	15 m^2	4 sensors

TR = triangulation, IM = imaging, FP = fingerprint, MD = model, PX = proximity.

Although Wi-Fi is moderately more expensive than the above technologies, it can cover a larger area with fewer devices, for example, an area of 750 m^2 can require only five Wi-Fi devices.

6 CHALLENGES AND FUTURE TRENDS

In this section, we first discuss the open challenges of DFI localization and tracking in a multi-resident environment and then we describe the future trends in DFI localization and tracking.

6.1 Open Challenges

6.1.1 Complex Scenarios in Multi-person Localization and Tracking. In general, persons need to stay in different areas or zones or to locate sparsely to facilitate localization and tracking tasks. However, DFI localization and tracking systems often operate in a small space, such as a small office or a living room, which introduces extra challenges: First, the measurement of one person can be interfered with by that of another person [29], which affects the accuracy of location estimation. Second, an occlusion occurs when persons are tightly close to each other [63, 128], resulting in the loss of targets. Although assumptions can be made such as treating multiple persons as a single one [9], assuming that the trajectories of persons remain unchanged, or assuming that persons are likely to return to specific locations such as desks [144, 152], such assumptions may not be practical in real-life situations. For example, two persons may meet and then leave in different directions. How to effectively and efficiently deal with the above-mentioned issues raised by complex scenarios remains an open challenge to researchers.

6.1.2 Variety and Identity of Targets. DFI localization and tracking systems are usually calibrated and trained with a single target. However, each person has individual physical properties such as weight, height, and width. These variations may lead to less-accurate results, as varieties of targets induce irregular measurements [153]. One of the solutions is to train the system using all possible targets. However, it is expensive and time-consuming. There is a work that used a transfer method to handle a diverse category of targets, but it still requires prior knowledge [153]. When there is a new target that does not belong to any category, it leads to inaccurate localization and tracking outcomes. Thus, the problem of a variety of targets is still not fully solved. To identify a person, each work used a certain type of localization and tracking technologies such as PIR [154], Wi-Fi [100], and electric field [16]. Different features have been extracted from measurements of chosen technologies to create profiles of persons. Some works used raw features such as an amplitude of signals [102], while the others extracted gait features [98–100]. However, different persons may have similar physical properties or behaviours so similar measurements and features are generated. Thus, it becomes problematic to identify resembling persons. In addition, a person may change their clothes and shoes daily, so it may cause some variations in measurements collected by the system and lead to inaccurate identification [16]. Thus, it remains an open challenge to effectively improve the accuracy of these two issues.

6.1.3 Scalability to the Number of Persons. Most existing works on DFI localization and tracking conducted experiments using different numbers of participants and the number of persons is known [77, 144, 145, 155]. However, the number of persons may be unknown and vary from time to time in real-life situations. This uncertainty can affect the performance of the system [156]. In real-world applications, the system may need to handle a large crowd in a large-scale area such as museums, shopping malls, and conference halls. Thus, the development of DFI localization and tracking approaches that can cope with a large crowd is still challenging [17].

6.1.4 Changes in an Environment. Changes in the environment are one of the factors that affect the performance of DFI localization and tracking systems. With the elapse of time, the performance of the system might degrade continuously [17]. For example, relocation of furniture can affect RF signals in some RF-based DFI localization and tracking systems. The systems need to be recalibrated and re-trained to keep up with all changes occurred in an environment. Thus, a huge amount of human effort is needed. Changes in an environment can happen for both single and multi-person localization and tracking. Some preliminary works addressed the problem using the less sensitive measurements such as CSI [33] and Differential RSS [117]. In addition, most existing works conducted experiments to evaluate their proposed solution for changes for a short period. However, these cannot ensure the performance of the systems in the long run. Online learning techniques that are incremental techniques that are capable of lifelong learning on a device with limited resources in real time may be a promising solution to this problem [157]. So far, we have found some works that have proved the feasibility and effectiveness of the online sequential extreame learning (OS-ELM) technique for a device-based indoor localization [158, 159]. Thus, how to effectively handle dynamic changes in the long run remains a challenging issue and needs to be further investigated.

6.2 Future Trends

6.2.1 Knowledge Transfer. DFI localization and tracking systems are calibrated and tested in a specific environment and setting. Whenever DFI localization and tracking systems are deployed in a new location, the system becomes less accurate as the previous calibration does not take into account changes in layouts and surroundings such as area size, furniture, and walls. As a result, we need to collect new data and recalibrate the system entirely. To reduce the human effort and time for collecting radio maps or fingerprints, one can transfer and reuse existing fingerprints from a current site to a new site. A transfer algorithm will map the radio maps from an original location to a new location based on the similarity of environments. In addition, knowledge about persons that are collected in the current location could be transferred. This could be particularly useful for the multi-occupancy setting. Some preliminary works attempted to realize this idea, such as in References [153, 160].

6.2.2 Self-adaptive Localization and Tracking System. Changes in an environment such as furniture relocation and room size adjustment can affect the accuracy of location estimation. Human effort is required to recalibrate parameters and recollect fingerprint databases. To tackle this problem, recent work on Wi-Fi technology can be adapt from a small area to a bigger area by mapping CSI distribution of references grids from a previous location to a new location and using reference grids to estimate CSI distribution for the rest of the new area [140]. As a result, it reduces time and human effort for collecting the fingerprint. Furthermore, online learning techniques such as OS-ELM have been employed in device-based solutions [158, 159]. We anticipate that online learning will be adopted in device-free solutions, too, because these techniques are particularly useful for high dynamic or large-scale areas that are inconvenient to collect new data, such as shopping malls. Therefore, we expect to see more DFI localization and tracking works that can adapt to cope with changes in the environment automatically in the future.

6.2.3 Deep Learning. Deep learning has been employed extensively in many fields, including speech recognition and computer vision over the past few years. Deep learning is capable of learning the right features and making an appropriate prediction without a domain expert or human intervention. It has been recently adopted in a field of DFI localization and tracking [24, 137]. The results show that deep learning can learn discriminative features automatically from RF signals. We believe that deep learning may potentially be useful for device-free localization in the multi-person setting. For example, deep learning techniques can be used to identify the most appropriate features and improve the accuracy of multi-resident localization and tracking.

6.2.4 Extending Localization and Tracking to Support Activity Recognition. Recently, techniques of DFI localization and tracking have been extended to recognize simple gestures. Recent works show that recognizing simple activities, such as standing, walking, and sitting are feasible [125, 137, 139, 161, 162]. In general, complex activities are composed of simple activities. Thus, we expect that further improved techniques will appear so that complex activity can be recognized such as cleaning and cooking.

7 CONCLUSION

Over the past year, device-free indoor localization and tracking have gained popularity. Although much research effort has been carried out in this area, the presence of multi-residence introduces several new challenges. In this article, we have presented an in-depth review of DFI localization and tracking with a focus on the multi-resident environment. We have comprehensively introduced technologies and techniques for device-free localization and tracking. The components of multi-resident localization and tracking were discussed, including human presence detection, target counting, target identification, localization, and tracking. For each component, we provided a classification of its related techniques as well as the details of these techniques. We have also discussed the performance metrics for device-free indoor localization and tracking. Finally, we identified the open challenges and future trends. We concluded thereby that our survey can benefit researchers in knowing the latest development in DFI localization and tracking as well as understanding the pros and cons of the state-of-the-art approaches and systems to develop novel approaches that outperform existing ones.

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