Indoor Positioning Technologies Without Offline Fingerprinting Map: A Survey

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***Abstract*—Fingerprint-based wireless indoor positioning approaches are widely used for location-based services because wireless signals, such as Wi-Fi and Bluetooth, are currently pervasive in indoor spaces. The working principle of fingerprinting technology is to collect the fingerprints from an indoor environment, such as a room or a building, in advance, create a fingerprint map, and use this map to estimate the user's current location. The fingerprinting technology is associated with a high level of accuracy and reliability. However, the fingerprint map must be entirely re-created, not only when the Wi-Fi access points are added, modified, or removed, but also when the interior features, such as walls or even furniture, are changed, owing to the nature of the wireless signals. Many researchers have realized the problems in the fingerprinting technology and are conducting studies to address them. In this paper, we review the indoor positioning technologies that do not require the construction of offline fingerprint maps. We categorize them into simultaneous localization and mapping; inter/extrapolation; and crowdsourcing-based technologies, and describe their algorithms and characteristics, including advantages and disadvantages. We compare them in terms of our own parameters: accuracy, calculation time, versatility, robustness, security, and participation. Finally, we present the future research direction of the indoor positioning techniques. We believe that this paper provides valuable information on recent indoor localization technologies without offline fingerprinting map construction.**

***Index Terms*—Indoor positioning, offline fingerprint map, SLAM, inter/extrapolation, crowdsourcing.**

I. Introduction

In THE 21st century, various mobile devices such as smartphones, tablets, and smartwatches have been developed, and they have been disseminated rapidly and widely [1], [2]. An increase in the number of mobile device users has led to the development of various services and applications based on the users' location, as determined by the mobile devices. The importance of positioning technologies that accurately capture the current location of a user has been well emphasized in various studies [3]–[10].

Positioning technologies are broadly classified into outdoor and indoor positioning technologies. The outdoor positioning technology uses global positioning system (GPS) signals [11]–[15]. However, GPS signals are satellite signals, which exhibit strong linearity, and are thereby subject to diffraction and reflection by buildings. Therefore, GPS signals cannot penetrate building walls and cannot be used for indoor positioning [16], [17]. The researchers have been studying various wireless media for indoor positioning, owing to this lack of availability of GPS [18]–[20].

The indoor positioning technologies use wireless fidelity (Wi-Fi) [21]–[24], Bluetooth [25]–[28], vision [29]–[31], geomagnetism [32], inertial sensors-based localization [33], [34], ultrawide band [35], radio-frequency identification [36], ultrasound or sound [37], [38], light [39]–[42], and pedestrian dead reckoning (PDR) [43]. Among these technologies, Wi-Fi has the most advantages as compared to other infrastructures. Its main advantage is universality. There is no need to install additional devices in the building or add additional parts to mobile devices. Furthermore, many individuals can use Wi-Fi with ease because it is a more familiar technology than other technologies. Thus, the Wi-Fi infrastructure has attracted the most research attention, producing the greatest number of extant studies.

Fig. 1 illustrates the taxonomy of indoor positioning techniques. In the early stages of a research in this field, the researchers performed indoor positioning using triangulation techniques that are already used outdoors. However, it is difficult to accurately determine the position indoors by triangulation, because of the obstacles in the room. Therefore, researchers chose to either improve upon the triangulation methods [44]–[48] or turn to fingerprinting techniques [49]–[52].

The fingerprinting technology is more accurate than triangulation or other technologies [53], [54]. However, it requires the preliminary step of offline fingerprinting map construction, which consumes a considerable amount of time and efforts. The fingerprinting map must be entirely re-constructed when the Wi-Fi access points (APs) are added, modified, or removed. Moreover, reconstruction of the fingerprint map is required whenever the interior features, such as walls or even furniture, are changed; because the changes in the wireless signal environment may warp the fingerprinting map.

To overcome these limitations of the fingerprinting technology, many researchers have conducted various studies. Extensive survey studies have reviewed and analyzed the various wireless indoor positioning approaches, and they present useful and valuable information on state-of-the-art technologies [55]–[65]. However, most of them focus only

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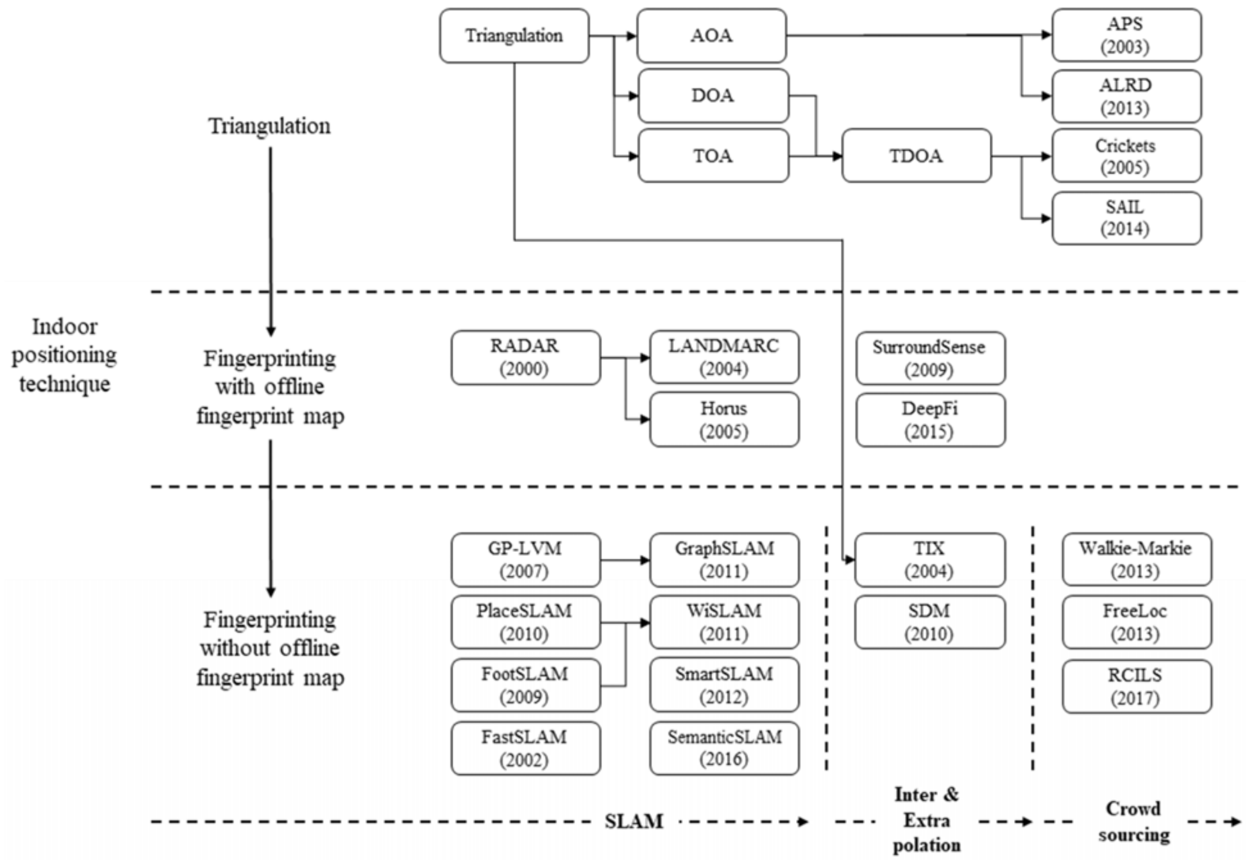


Fig. 1. Taxonomy of indoor positioning technologies.

on fingerprint-based approaches. We can argue that the efforts required for offline fingerprint map construction are extremely labor-intensive, because indoor spaces are often enormous and complex, and they require repeated measurements.

The purpose of this study is to present a timely, valuable, and detailed comparison of indoor positioning technologies that do not require the construction of offline fingerprint maps. We categorize them into simultaneous localization and mapping (SLAM) [66], [69]–[71], inter/extrapolation [72], [73] and crowdsourcing-based technologies [67], [76]–[82], and describe their algorithms and characteristics, including advantages and disadvantages. The SLAM technique creates a map of an unknown environment and keeps tracking the user's position in real time with the estimated location of the person and the landmark of the environment. Many SLAM techniques have been applied to indoor location positioning, owing to their effectiveness and wide employment in various fields, such as self-driving cars, unmanned aerial vehicles, and robotics [68]. In this study, we survey the Gaussian process latent variable model (GP-LVM) [69], GraphSLAM [70], and WiSLAM [71]. Other studies focused on the location of APs rather than the use of SLAM technologies. They calculate the locations of APs and estimate the position of a user without offline fingerprinting map construction. Triangular interpolation and eXtrapolation (TIX) [72] and signal distance map (SDM) [73] are presented and discussed in this study. The increasingly widespread use of mobile devices within the population has led to the use of crowdsourcing technologies to construct a building map by obtaining data from users by exploiting a multitude of systems in a device [74], [75]. With the crowdsourcing technology, a user constructs a map using crowdsourced information and simultaneously provides information [76]–[82]. In this study, we review Walkie-Markie [81] and robust crowdsourcing-based indoor localization system (RCILS) [82]. We compare them in terms of our own parameters: accuracy, calculation time, versatility, robustness, security, and participation. Finally, we present the future research direction of the indoor positioning techniques.

The remainder of this study is organized as follows. We present the concept and problem of localization techniques and fingerprinting techniques in Section II. In Section III, the SLAM series techniques are described in detail. Section IV presents the inter/extrapolation techniques. In Section V, we present the crowdsourcing-based technologies. Section VI analyzes the surveyed techniques based on important criteria. In Section VII, we present the future research direction of the indoor positioning techniques, and Section VIII concludes our study.

II. Background

A. Localization Techniques

Localization techniques ascertain the position or location of a stationary or moving person. In outdoor environment, most systems or services based on a user's location use GPS.

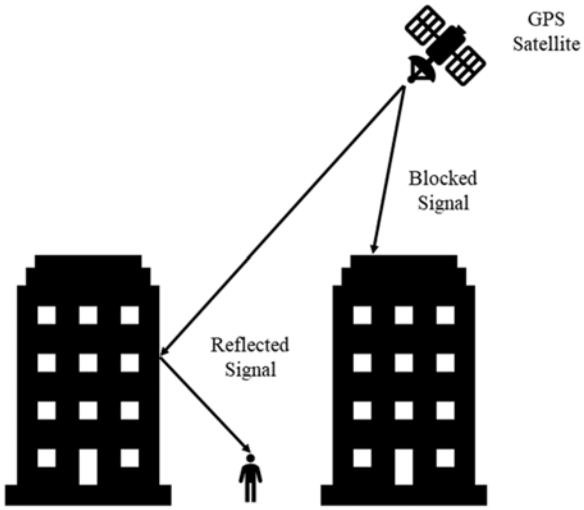


Fig. 2. Blocked and reflected GPS signals. The devices cannot receive GPS signals in indoor environment because of this phenomenon.

GPS is the satellite signal-based navigation system [83]. GPS receives signals from more than three satellites. Thus, it can accurately estimate the current location of a user through trilateration by the rear intersection, using three different distances. The accuracy of GPS is within 4.9 m (16 ft.) radius under open sky [84]. However, in an indoor environment, we cannot use GPS. Fig. 2 shows the reason for this phenomenon. The GPS signals are carried through waves, which have a frequency that does not move easily through solid objects, such as walls of buildings. Thus, unfortunately, the GPS signals cannot penetrate such kind of barriers with ease, which makes it useless in indoor positioning.

The triangulation process with indoor infrastructure is one of the techniques that helps fill this vacant space of GPS. GPS uses a triangulation. Thus, researchers graft triangulation with indoor infrastructure, such as Bluetooth [85]. The indoor triangulation process measures the location of a user through the following process. First, the user's mobile device catches the wireless radio signals emitted by the indoor infrastructure. Further, the device selects three strongest signals from the same. The device calculates the distances between the infrastructure and the device using the strength of the selected signals. Finally, the device estimates the location of the user with the calculated distances. The triangulation process can be understood easily and is effective when it is used to measure location in a wide range. However, triangulation has several shortcomings concerning indoor localization. It cannot be used in an environment with less than three infrastructures. Moreover, it is dependent on signal strength. However, in an indoor environment, there are obstacles and room partitions that impede the smooth reception of signals and accurate measurement of signal strength. This causes a major error in distance calculation. Therefore, triangulation does not work well indoor with obstacles and room partitions. As a result, researchers have discovered a new technique, the fingerprinting technique.

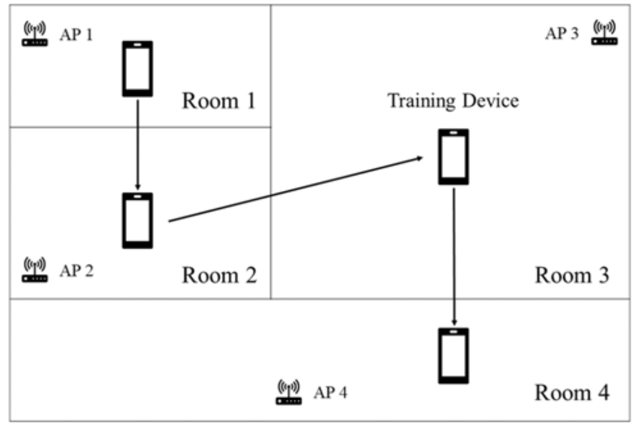


Fig. 3. Offline training phase.

Location	RSS(in dBm)			
	AP 1	AP 2	AP 3	AP 4
Room 1	**-90**	**-70**	**-60**	**-50**
Room 2	**-70**	**-90**	**-55**	**-70**
Room 3	**-60**	**-50**	**-85**	**-50**
Room 4	**-40**	**-50**	**-60**	**-90**

Fig. 4. Radio map based on the fingerprint information.

B. Fingerprinting Technique

The fingerprinting technique is more accurate than the conventional infrastructure-based indoor positioning technologies, including triangulation technologies [86], [87]. It uses the existing infrastructure, such as Wi-Fi, to provide location-based services (LBSs) [88], [89]. This means that the fingerprint technology does not involve the installation of new infrastructure or hardware, thereby saving time and money.

Fingerprinting-based systems involve two phases: the offline training and online location estimation phases. Fig. 3 shows the offline training phase. In the offline training phase, the user moves in a room with various mobile devices, such as smartphone, tablet, and smartwatch. When the training device selects a position of interest from the movement path, the device collects a fingerprint of the position, in the form of received signal strength (RSS). Subsequently, the device creates a radio fingerprint map based on the fingerprint information, as shown in Fig. 4. Fig. 5 shows the online location estimation phase. In the online location estimation phase, the user moves in a room with the client device. The fingerprint measured by the client device is sent to the positioning engine within the client device. The positioning engine compares the observed fingerprint with the map produced during the offline training phase and returns the best match. However, three problems are associated with the fingerprint technique, which include time consumption, error in receiving RSS, and vulnerability to environmental changes.

First, the fingerprinting technology includes a prerequisite, whereby fingerprints should be collected in the room in advance [90]. This means that the fingerprint must be collected

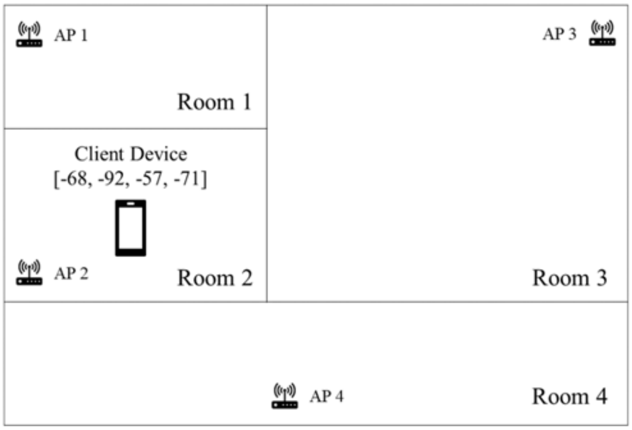


Fig. 5. Online location estimation phase.

using the training device well in advance. This activity consumes a considerable amount of time and efforts [91], [92].

Second, the accuracy and precision provided by the existing fingerprinting map should not change, even when unexpected changes in the environment occur. For example, a location error of 2–3 m is relatively small in an outdoor environment. In an indoor environment, with such an error, the client device might indicate that the user is beyond the original position or beyond the wall based on the surrounding environment and time [93]. Thus, indoor positioning technologies require a high level of accuracy at any given time or setting. However, it is difficult for the fingerprint technology to satisfy this requirement because the phenomenon involves multipath propagation [94]. Contrary to the outdoor environment, the radio signals are reflected, attenuated, diffracted, or extinguished indoors by various obstacles, such as walls, pillars, and individuals. Considering this mode of propagation, several errors are caused, even in the conversion from RSS to distance.

Finally, applications and services that use an existing fingerprinting map cannot use an old map if even a single AP is added, replaced, or modified in the indoor environment. Small changes to the indoor structures, including walls or even furniture, may nullify the usefulness of an existing fingerprinting map. In such a case, a new fingerprinting map will have to be created from scratch. This requires considerable time and effort again. Furthermore, the replacement or modification of an AP and changes to indoor structures are not rare. Hence, the use of offline fingerprint maps may impose a great burden.

III. SLAM SERIES TECHNOLOGIES

A. SLAM

The SLAM technique is used by mobile robots to build a consistent map of an unknown environment, while simultaneously determining its location within the built map [95]. In SLAM, both the path of the person and the location of the landmarks are estimated online without the need of any previous knowledge of the environment or location.

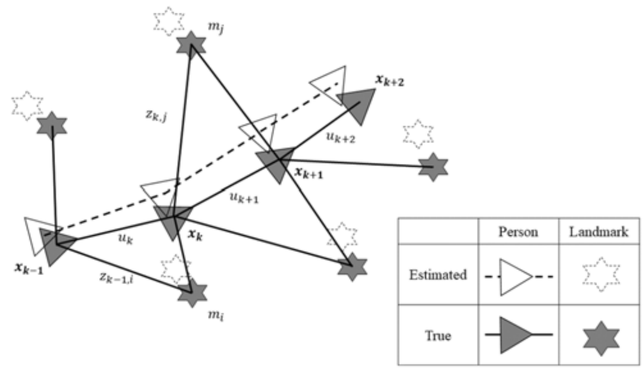


Fig. 6. Essential SLAM problem.

Fig. 6 shows the movement of a person through an environment, who checks the relative observations of the unknown landmarks with a device. At time k, the following values are defined. x_k is the state vector that indicates the orientation and location of the person. u_k is the control vector applied at time k-1 to estimate a state x_k, which is the next location of the person at time k. m_i is the vector describing the location of the i^{th} landmark, which is assumed to be the true location at the same time. z_{ik} is the observation taken from the person of the location of the i^{th} landmark at time k.

Along with the above values, the following sets can be generated. $X_{0:k} = \{x_0, x_1, \ldots, x_k\} = \{X_{0:k-1}, x_k\}$ is the set of the passed person's locations. $U_{0:k} = \{u_0, \ u_1, \ldots, u_k\} = \{U_{0:k-1}, u_k\}$ is the set of the control inputs. $\mathrm{m} = \{m_1, m_2, \ldots m_n\}$ is the set of all landmarks. $Z_{0:k} = \{z_0, z_1, \ldots z_k\} = \{Z_{0:k-1}, z_k\}$ is the set of landmark observations

SLAM estimates the location of user using the above values. Thus, SLAM requires the probability distribution for all times k.

$$\mathrm{P}(x_k, m | U_{0:k}, Z_{0:k}, x_0) \tag{1}$$

The probability distribution shows the joint posterior density of the landmark's location and person's state at time k when the recorded observations, control inputs, first state of the person, and time k are given. Generally, a recursive solution is advisable in SLAM.

The joint posterior is calculated by the Bayes theorem [96] with a control input u_k and observation z_k, starting from the estimation of the distribution $\mathrm{P}(x_{k-1}, m | U_{0:k-1}, Z_{0:k-1})$ at time k − 1. The calculation needs to define the state transition model $\mathrm{P}(z_k | x_k, m)$ and the observation model $\mathrm{P}(x_k | x_{k-1}, u_k)$, which describe the effect of the control input and observation individually.

The SLAM algorithm is implemented in a standard two-step recursive (sequential) prediction (time-update), and correction (measurement-update) form. The time-update is calculated as follows:

$$\mathrm{P}(x_k, m | U_{0:k}, Z_{0:k}, x_0) = \int \mathrm{P}(x_k | x_{k-1}, u_k) \times \mathrm{P}\big(x_{k-1}, m | U_{0:k-1}, Z_{0:k-1}, x_0\big)\, dx_{k-1} \tag{2}$$

The measurement-update is calculated as follows:

$$\mathrm{P}(x_k, m | U_{0:k}, Z_{0:k}, x_0) = \frac{\mathrm{P}(z_k | x_k, m)\mathrm{P}\big(x_k, m | U_{0:k}, Z_{0:k-1}, x_0\big)}{\mathrm{P}\big(z_k | U_{0:k}, Z_{0:k-1}\big)} \tag{3}$$

Equations (2) and (3) show recursive operations for calculating the joint posterior about the state x_k and map *m* at time k based on all control inputs $U_{0:k}$, observations $Z_{0:k}$, and time k. The map is constructed by merging the observations from different locations. Moreover, the state may be formulated by computing the probability distribution. The researchers applied this technique for indoor localization and obtained the following techniques.

B. GP-LVM

Ferris *et al.* [69] introduced GP-LVM, which maps a three-dimensional (3D) data to two-dimensional (2D) potential space. The 3D data correspond to the signal strengths of all the APs in the environment, and GP-LVM maps the data to a 2D space that is interpreted in terms of x and y coordinates.

Generally, when the user performs indoor positioning by fingerprinting, the client device measures the signal strengths of the APs and stores them in the fingerprint map. Further, based on the generated fingerprint map, the client device compares the values of APs measured by the user's device with the values of APs stored in the fingerprint map to estimate the user's current location. However, in this conventional fingerprinting method, the stored AP values are fixed, and they cannot reflect any changes of the indoor environment.

GP-LVM does not store the signal strength of AP as fixed location information. It treats the measured data as a latent variable. Subsequently, it stochastically models the relationship between the stored latent variable and the actual data measured by the client device and restores them through the optimization of the marginal likelihood. GP-LVM has three pre-requisites. First, APs that are located close to each other possess similar signal strengths, and the value of each signal strength is unique at distinct locations. Second, similar values of a signal strength are measured at close location to each other. GP-LVM requires this condition for detection when the loop of the path is closed (i.e., when the individual returns to a previously visited location). Finally, the locations that are sequentially measured in the data stream should be close to each other. This constraint models a fact that the data is collected by a person who walks through the building. Further, the path data prior to measurement is absent; thus, a user must additionally set the internal conditions of the building. While constructing a building model, the following three conditions should be set: the distance between consecutive positions, change in orientation between successive postures, and alignment of parallel line segments.

Thorough experiments were conducted on one floor of a university building to verify the GP-LVM. Data from three paths with path lengths ranging from 250–500 m were collected. The AP data were collected using a handheld iPAQ [97], a standard Wi-Fi card, and a click-to-map-based annotation program to set the ground truth path. The movement path included three rooms and corridors of the building. Fig. 7 shows that GP-LVM presents the precise alignment of intersections and paths between corridors, although the structure of the building was not clarified in advance. The GP-LVM shows an error of 3.97 m in the test bed. However, the GP-LVM involves several problems. It requires the time complexity of O(n^3); thus, it is difficult to operate it online on mobile devices. Additionally, it is difficult to apply GP-LVM in universal locations, given that the constraints of the place should be set in advance. The GP-LVM also tends to compensate the produced map by using straight lines and right angles. The curved portion of the ground true path of the building is displayed only with straight lines and right angles on the produced map, as shown in Fig. 7.

C. GraphSLAM

The GraphSLAM technology is commonly used for simultaneously estimating a trajectory and building a map offline [70]. GraphSLAM presents the parameterization of an indoor environment for typical mobile device applications.

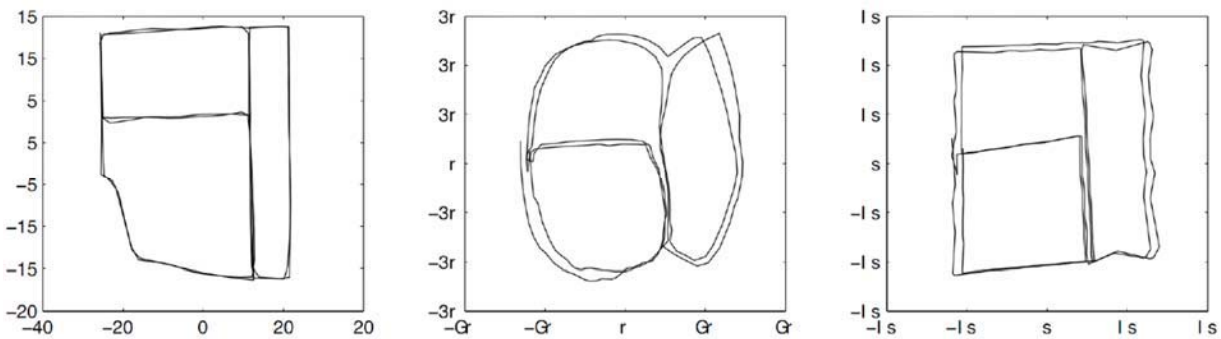
GraphSLAM does not consider the effect of signal density or the weakness on the signature uniqueness as important. The measurement results of the signals are attracted to similar adjacent measurements, except for the vector of all signal strength measurements. This feature provides sufficient information to reinforce the existing SLAM implementation, even if the signal is not sufficiently rich to guarantee the uniqueness of the wireless signature. GraphSLAM incorporates the low-cost inertial measurement unit (IMU) [98] data to provide SLAM solutions for both linear corridor and open atrium environments [99]. The data are used to introduce motion measurement capabilities into a common sensor model that is applied to a common crowdsourcing application. At most distances from a transmission node, GraphSLAM expects that all propagated radio waves have almost the same strength with any small region of free space. However, this relationship between nearby signal strengths in a wider area depends highly on a building's structure and architectural style. To complement this, GraphSLAM simply interpolates a small area that can correspond to free space in the absence of a model for the building structure.

GraphSLAM is formulated as a network of Gaussian constraints between positions of user x_t and landmarks of environment m_t at time t. For each measurement Z_i from any sensor in device, the state-measurement mapping function $h_i(\mathbf{X})$ shows true measurements if the values of the state variables (x_t, m_t) were as follows:

$$Z_i = h_i(\mathbf{X}) + \varepsilon_i \tag{4}$$

where $\mathbf{X} = \{x_{t1}, x_{t2}, \ldots, m_{t1}, m_{t2}, \ldots\}$ is the collection of all states and variables. ε_i is the noise added at the time of measurement. With the state-measurement mapping function $h_i(\mathbf{X})$, we can express the motion model of GraphSLAM. For example, in measurement with a pedometer between time t_i and t_{i+1}, the measurement is related to the state space by the following function:

$$h_i^{pedometer}(\mathbf{X}) = \left\| x_{t_{i+1}} - x_{t_i} \right\|_2 \tag{5}$$



(a) Actual path (b) Isomap technology (c) GP-LVM

Fig. 7. Experimental results maps of movement in a building [69].

Similarly, in measurement with a gyroscope, the measurement is related as follows:

$$h_i^{gyroscope}(\mathbf{X}) = \frac{atan2\left(x_{t_{i+1}} - x_{t_i}\right) - atan2\left(x_{t_i} - x_{t_{i-1}}\right)}{\Delta t} \tag{6}$$

where $\Delta t = (t_{i+1} - t_{i-1})/2$.

For each sensor, the GraphSLAM measurement likelihood function is described by the definition of the state-measurement mapping $h_i(X)$ with the variance of the corresponding sensor noise $\sigma_\varepsilon = Var(\varepsilon)$.

While the user is moving, the position of the user is x and the measurement time of the i^{th} landmark is t. At each time t_i in the user's path, the user has an inferred subjective location x_{t_i} deduced from GraphSLAM and a true objective location $x_{t_i}^*$ for the same time stamp in the ground truth path. Considering each objective location $x_{t_i^*}^*$, the objective neighbors are marked by a point in *r* meters of $x_{t_i}^*$. The moved distance between consecutive signal searches is given by *r*. Considering each objective neighbor of $x_{t_i^*}^*$, the subjective location x_{t_i} has a corresponding subjective neighbor $x_{t_i^*}$. The GraphSLAM output is extended such that the total moved distance matches with the total moved distance of the ground truth path. The localization error is defined to be the mean of the distance that defines the average of the distance $\|x_{t_i} - x_{t_i^*}\|_2$ in all pairs $(t_i,\ t_i^*)$.

For verifying GraphSLAM, researchers used 536 Wi-Fi scan traces captured over 17 min on one floor of a 60 m × 10 m university building, which is approximately 1.2 km in length. Fig. 8 shows that the results are very similar to those obtained for the ground truth path, although GraphSLAM does not require setting the interior shape in advance. The average localization error for pedometer and gyroscopes, as measured without Wi-Fi, is 7.10 m. Contrarily, GraphSLAM uses the same metric for comparison and exhibits an average localization error of 2.18 m.

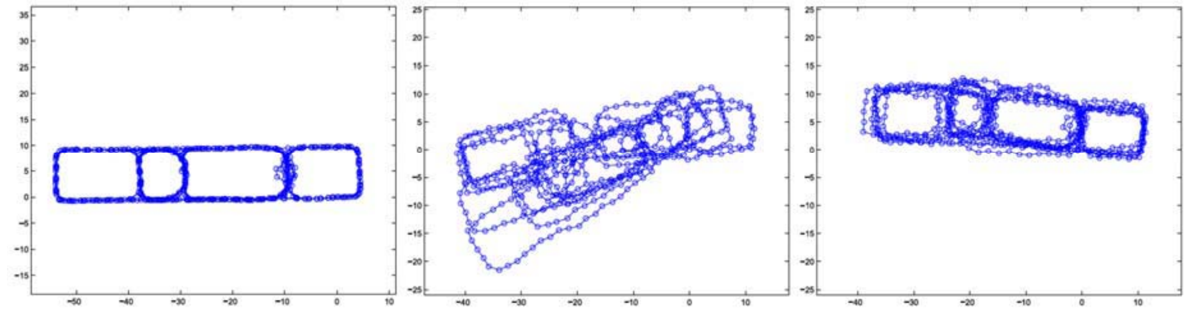
GraphSLAM is developed to overcome the drawbacks of GP-LVM and to be used in a wider and more general indoor environment. When creating a large map, GraphSLAM requires only $\mathrm{O(n^2)}$ operations for each iteration. It does not require set conditions, even if the internal information about the building is absent. However, its disadvantage is that $\mathrm{O(n^2)}$ time-complexity remains arduous with respect to operation on mobile devices, and it can be applied only in offline mode. Further, GraphSLAM has a constraint that it expects the propagation of a signal to have the same intensity in a small region of free space. In the case of a wide space, where the above condition is not applied, there is a problem that the large space needs to be interpolated into multiple small spaces to overcome this limitation. If the interpolating of the space is performed incorrectly, the result can be much lower than the desired performance.

D. WiSLAM

WiSLAM is an indoor location positioning technology that integrates PlaceSLAM, which performs indoor location measurement through measured RSS values, and FootSLAM, which performs indoor location measurement using an accelerometer [71], [100], [101]. FootSLAM uses the Bayesian estimation approach and a particle filter [102]. The implementation of FootSLAM involves the use of Rao–Blackwellized particle filter (RBPF) [103], and each particle of the particle filter consists of a user path instance and its associated map. The latter is obtained by dividing the applied location into hexagonal cells and estimating all conversion probabilities of the path. Extensive experimental results revealed that the convergence of mapping and localization occurs when a user uses up to 10,000 particles along a closed loop.

In PlaceSLAM [100], the location where the user's position is well recognized, and the proximity information related to the same is assumed. The complexity increases sharply when PlaceSLAM is associated with FootSLAM, although the convergence is significantly faster. Contrary to PlaceSLAM, WiSLAM provides the distance as opposed to proximity information in RSS measurements. In PlaceSLAM, a user must detect the proximity information manually, although the value measured by WiSLAM is fully automatic.

WiSLAM first represents the pedestrian behavior by using a dynamic Bayesian network (DBN) [104], as shown in Fig. 9. The RSS is subsequently measured. At this time, it is assumed that the RSS of different APs are independent of the user's location, and WLAN maps of APs are also independent of each other. Under this assumption, we calculate the contributions of each AP separately and integrate them at the



(a) Ground truth path (b) Pedometer and gyroscope only (c) Converged GraphSLAM path

Fig. 8. Comparison of positioning tracking results [70].

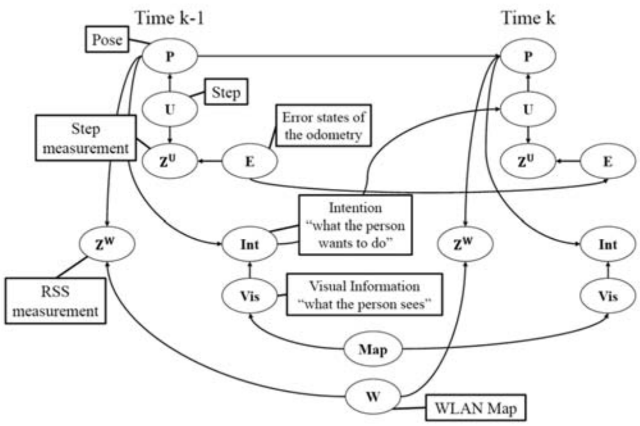


Fig. 9. Dynamic Bayesian network for WiSLAM.

end. Additionally, different RSS measurements measured at the same AP are conditionally independent. Subsequently, WiSLAM derives this measured value with the Bayesian filter. Finally, the operation of WiSLAM is completed after WiSLAM learns the map.

For verifying WiSLAM, a wide range of real data measurements were performed in an indoor space of approximately 20×40 m. A laptop equipped with Link 5100 and an internal network device conforming to IEEE 802.11 a/b/g [105] are used for the experiment. The APs used for the experiment are in compliance with Cisco Aironet 1130 and IEEE 802.11 a/b/g. For realistic scenarios, the researchers collect 10 datasets in the same path during the day time when the APs are the most active.

As shown in Fig. 10, the probability density function of the location of AP is depicted through density plots at $k = 1$, 3, 5, 7, 9, and 11, where the darker shade indicates higher values. The standard signal strength emitted by the previously known AP and the standard deviation of the RSS are assumed as 5 dB. Fig. 11(a) illustrates a test space, showing the location of an AP (green rectangle) for SLAM and two competing paths (successive blue paths). Fig. 11(b) shows the normalization of Fig. 11(a). The actual path is indicated by blue circles. The result of the above experiment shows a large error because the RSS of only one AP is used. However, the accuracy of WiSLAM increases when several APs are used.

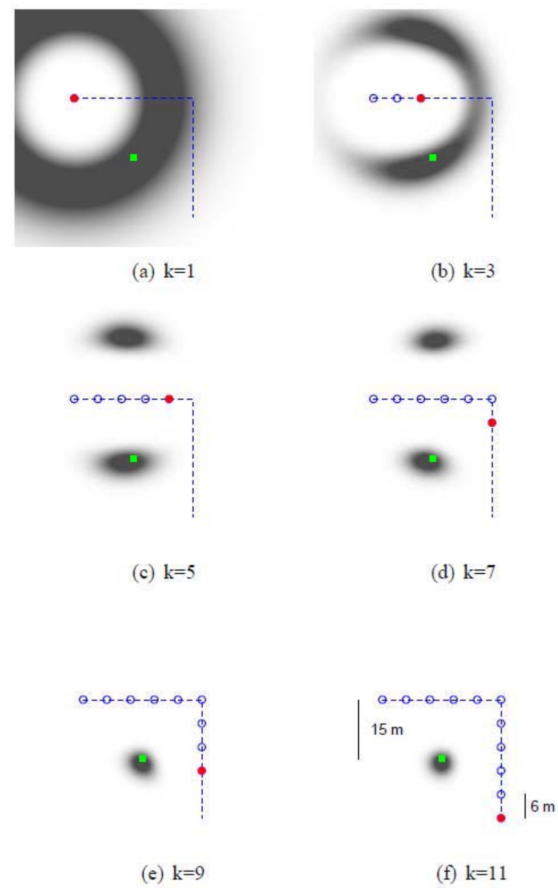


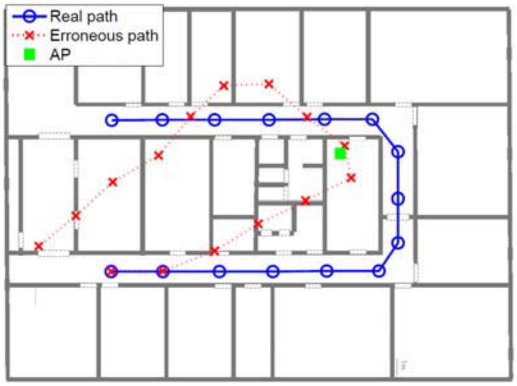
Fig. 10. Simulation results based on assumption and algorithms [71].

WiSLAM achieves a position accuracy of 5.4 m in an indoor environment of 800 m^2. WiSLAM combines two SLAMs, which is more accurate than two SLAM schemes. However, considering that two SLAMs are collectively used, the computation process is rather complicated, which becomes a disadvantage because it becomes difficult to operate on an online device.

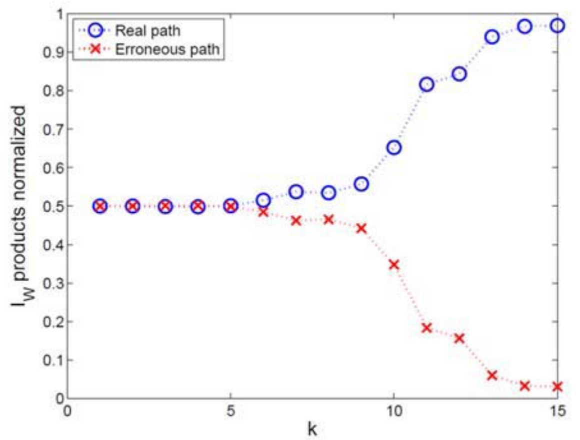
IV. Extrapolation and Interpolation

A. TIX

TIX captures the user's position using RSS values measured from at least three APs [72]. Fig. 12 shows the basic



(a) Experimental space



(b) Normalization for two paths

Fig. 11. Experimental results [71].

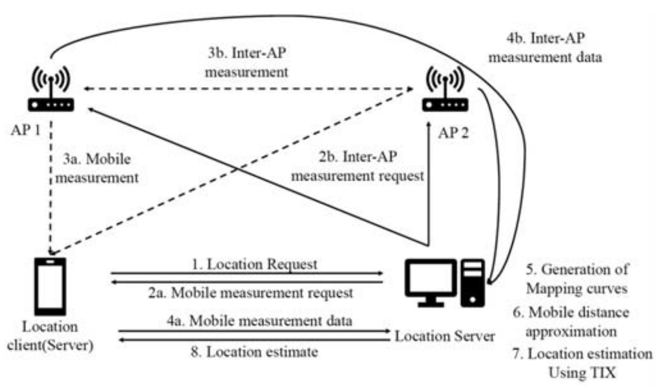


Fig. 12. Architecture of TIX.

architecture of TIX. The client sends a location query to the location server. After receiving the query, the location server sends requests to the client and all APs to retrieve RSS measurements from all APs apart from themselves. For example, a client sends a location query to a location server in an environment with n APs. In this case, each AP reports the RSS values of the other (n − 1) APs, and the client reports n RSS measurements that includes all the APs. Further, the location server uses the measurements between the APs to generate multiple distance mapping curves for each observed AP. The generated curve maps the RSS values to the distance from the observed AP.

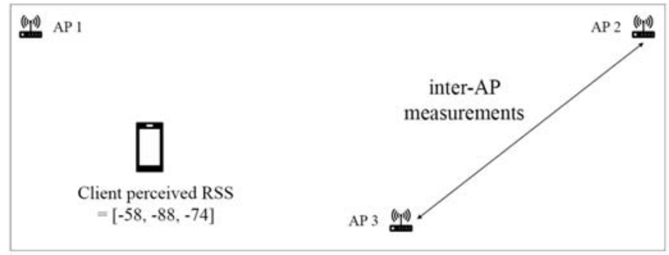


Fig. 13. Proximity in signal space.

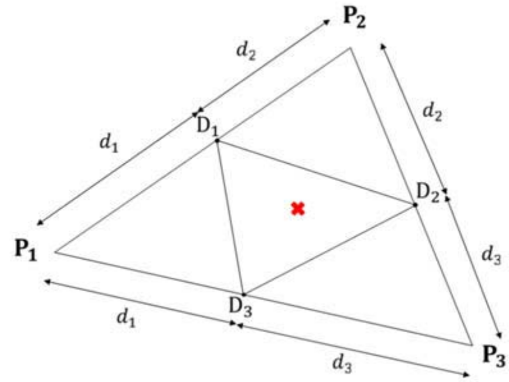


Fig. 14. Triangular interpolation.

After creating the mapping curves, the location server estimates the distance between each AP and the client using the appropriate mapping curve and RSS measurements. The server uses a simple heuristic called proximity in signal space (PSS) to select the appropriate mapping curve. PSS generates a mapping curve using the measurements of other APs, as measured by the AP that reports the highest value to the client.

For example, Fig. 13 assumes that the RSS values of AP 1, 2, and 3 measured by the client are S1, S2, and S3, respectively. If the order of intensity at this time is S1 > S3 > S2, as shown in Fig. 9, the server estimates that the client is closest to AP 1. Thus, the server approximates the distance between the client and AP 2 and 3 through a mapping curve generated using each RSS value that AP 1 measures. However, AP 1 does not measure its own RSS value; thus, the server generates a mapping curve of AP 1 using RSS of AP 1 measured at AP 3, which sends the second highest measurement value. The server estimates the final location of the client through the approximate distance between the AP and client calculated using the mapping curve and the location coordinates of the AP. Thus, the server uses the TIX algorithm. The TIX algorithm requires at least three APs. If there are three or more APs, then TIX choose the three optimal APs. TIX first forms a triangle with the positions of APs as vertices. Further, TIX uses the inner or outer divider of the sides of the triangle to estimate the final position of the client. In this case, two cases, triangular interpolation and extrapolation, are determined by the following conditions.

Fig. 14 shows the TIX algorithm with an internal divider (i.e., triangular interpolation). The vertices P_1, P_2, and P_3 of the triangle are the positions of the three APs AP 1, 2, and 3, respectively. The plane of triangle $P_1P_2P_3$ is internally

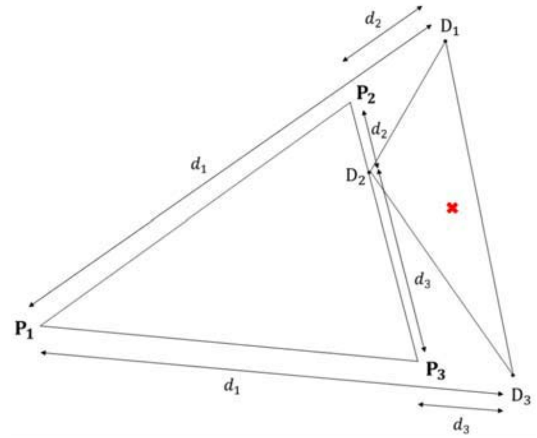


Fig. 15. Triangular extrapolation.

divided by points D_1, D_2, and D_3. The location server provides the center of triangle $D_1D_2D_3$ as the final position estimate. If the length of side P_1P_2 of triangle $P_1P_2P_3$ exceeds d_1, then it is possible to obtain the distance between AP 1 and the client and d_2, distance between AP 1 and the client, and point D_1 that divides P_1P_2 by the ratio $d_1 : d_2$, using the following expression:

$$D_1 = \frac{P_2 d_1 + P_1 d_2}{d_1 + d_2} \tag{7}$$

where D_1 includes the coordinates (D_{1x}, D_{1y}) of the internal divider, and P_1 and P_2 are the positional coordinates (P_{1x}, P_{1y}), (P_{2x}, P_{2y}) of AP 1 and 2, respectively. At this time, the length of d_1 is longer than d_2.

In the case of AP 2 and 3 and in the case of AP 1 and 3, the server determines the points D_2 and D_3, which internally divide P_2P_3 and P_3P_1 based on the conditions in the previous step. The center coordinates of the triangle $D_1D_2D_3$ formed by the points D_1, D_2, and D_3 as obtained through the previous process corresponds to the final estimates positions of the current client.

Fig. 15 shows the TIX algorithm with an external divider. In this case, the two sides of triangle $P_1P_2P_3$ corresponding to P_1P_2 and P_1P_3, are externally divided by the points D_1 and D_3, respectively, and the side P_2P_3 is divided internally. The center of triangle $D_1D_2D_3$ is given as the final position estimate. If side P_1P_2 of the triangle $P_1P_2P_3$ is shorter than d_1, then it is possible to obtain the distance between AP 1 and the client and d_2, distance between AP 1 and the client, and point D1 that divides the extension line of P1P2 by the ratio $d_1 : d_2$, using the following expression:

$$D_1 = \frac{P_2 d_1 - P_1 d_2}{d_1 - d_2} \tag{8}$$

where D_1 is the coordinates (D_{1x}, D_{1y}) of the external divider, P_1 and P_2 are the positional coordinates (P_{1x}, P_{1y}), (P_{2x}, P_{2y}) of AP 1 and 2, respectively. At this time, the length of d_1 is longer than d_2. In the case of AP 2 and 3 and also in the case of AP 1 and 3, the server determines points the D_2 and D_3 that internally or externally divide P_2P_3 and P_3P_1 according to the conditions in the previous step.

Specifically, TIX includes a position error of 5.4 m in an indoor environment with an area of 1020 m^2. Thus, TIX does not need a floor plan in advance because it uses only the location information of the APs. However, the disadvantage of TIX is that the calculation process becomes complicated and time-consuming when the number of APs increases. Furthermore, TIX cannot be used if the number of APs is less than three.

B. SDM

SDM is an indoor positioning technology for locating a client device by using RSS values measured online in the same manner as TIX [73]. The operating principle of SDM is similar to that of TIX, because it uses inter-AP measurements to obtain the mapping function. However, the algorithmic computation differs from TIX in several respects. When data is received from the m APs, SDM commences the calculation as follows:

$$e_i = \sum_{k=0}^{m} (\log(d_{ik} - b_i s_{ik})) \tag{9}$$

where d_{ik} denotes the distance between i^{th} $(i = 1, 2, \ldots, n)$ AP and each k-th $(k = 1, 2, \ldots, n)$ AP $(d_{ii} = 0)$, and s_{ik} denotes the RSS of k-th AP that is acquired by the i^{th} AP $(s_{ii} = 0)$. As a result, the coefficient vector b_i is solved as follows:

$$b_i = \log\left(d_i^T\right) S^T \left(SS^T\right)^{-1} \tag{10}$$

Using this, SDM can be expressed as follows:

$$B = \log(D) S^T \left(SS^T\right)^{-1} \tag{11}$$

where $D = [d_1, d_2, \ldots, d_m]$ denotes a matrix of geographic distances, and $d_i = [d_{i1}, d_{i2}, \ldots, d_{im}]^T$ denotes a vector of geographic distances. In the location determination step, the client measures the RSS from neighboring APs and searches for coefficients b_i associated with each AP i. Subsequently, the geographical distance to the adjacent AP i in the client is calculated as follows:

$$d_i = \exp(B s_i) \tag{12}$$

Thereafter, the server calculates the final estimated position of the client using the geographical approximation to the distance approximation from each AP to the client.

The localization accuracy is within 3 m in a small department building, and this exceeds that of TIX. However, contrary to TIX, SDM may require some pre-deployment efforts in the AP distance mapping step. Additionally, the calculation is complicated in comparison to TIX, and the calculation time is relatively high because all APs are calculated.

V. Crowdsourcing

A. Walkie-Markie

Walkie-Markie is a crowdsourcing-based indoor positioning system that automatically generates an indoor map of a building by combining the users' trajectory obtained with the smartphone's inertial sensors with special landmarks called as

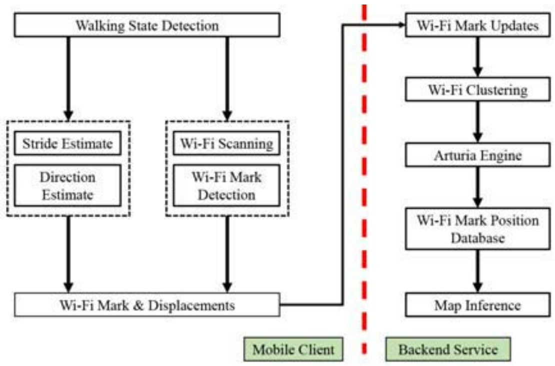
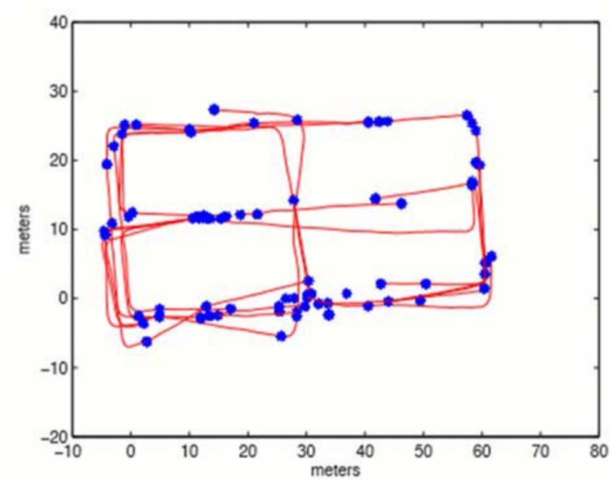


Fig. 16. System architecture of Walkie-Markie.

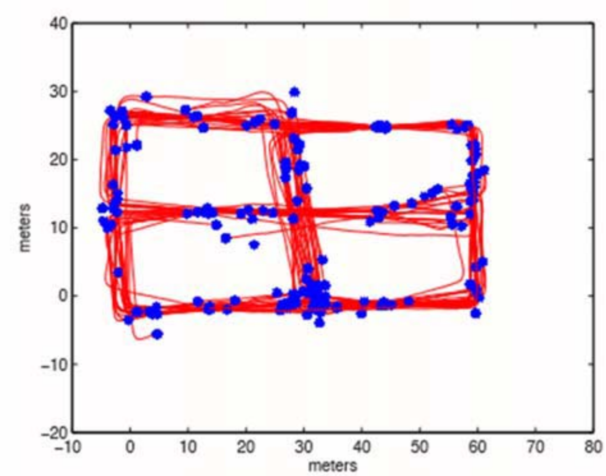
Wi-Fi marks [81]. Fig. 16 shows the system architecture of Walkie-Markie. Walkie-Markie consists of the mobile client in user's smartphone and the back-end-service in the cloud. When the user moves, the client collects regular Wi-Fi scan results and approximate trajectory information such as number of steps, stepping cycle, and direction of travel. The client generates Wi-Fi marks from the collected results and places them in a 2D map. The back-end-service uses the user's data to create a pathway map.

When a user with a smartphone moves, the mobile client measures the user's stride and direction by using IMU built in the smartphone. It simultaneously scans for signals and uses them to detect Wi-Fi marks. A Wi-Fi mark is a special location termed as a RSS trend tipping point (RTTP), in which the trend of signal strength changes from increasing to decreasing. The reason for using RTTP to for the Wi-Fi mark is that it is relatively free from heterogeneity among different mobile devices and other environmental factors that affect RSS. The mobile client deploys the Wi-Fi marks by applying the gathered stride and movement direction information of the client device to the positioning algorithm. Further, the client passes the deployed Wi-Fi marks to the back-end-service. In the back-end-service, the service updates the Wi-Fi marks. The Wi-Fi marks can be deployed differently (i.e., in different locations) by multiple crowdsourcing paths, and thus the server uses clustering algorithms to cluster various Wi-Fi marks into a single Wi-Fi mark. A major challenge in the Walkie-Markie system involves correcting the inaccuracy of IMU-based displacement measurements such as stride or directional errors. To compensate for these errors, the back-end-service uses the Arturia algorithm [106], which removes the noise of IMU measurements and assigns optimal coordinates to the Wi-Fi marks. After calibration with the Arturia algorithm, the service obtains and places Wi-Fi marks inside the 2D plane with the graph insertion algorithm using the path of the client device.

Researchers conduct some experiments in offices with conference rooms, cubicles, and large open spaces to test the system. The internal area of the office is 3600 m^2, and the total length of the internal passage is 260 m. A person moves through the passageways and spaces in the office with the client device. The quality of the path map is improved by information related to more users as shown in Fig. 17. After randomly walking for 100 min, the result map in Fig. 17(b) is very close to the actual path.



(a) Path map made from 40 minutes after starting the movement



(b) Path map made from 100 minutes

Fig. 17. Path maps sorted by path data of different users. The blue stars located on the path are Wi-Fi marks [79].

The average position error of Walkie-Markie is 1.65 m. Walkie-Markie does not require any conditions for the map construction. The only assumption of Walkie-Markie is that the environment must deploy APs, which is necessary for the operation of the system. However, it does not require knowledge of their locations. Additionally, IMU is used to increase the accuracy of the localization and to further enhance its reliability with various algorithms. However, Walkie-Markie operates depending on the data acquired by IMU at the beginning of the system, and therefore the sensor or the device itself may receive incorrect data due to failure. In this case, it significantly differs from the data obtained by other users; thus, it is difficult to generate an accurate path map.

B. RCILS

RCILS is a crowdsourcing-based indoor positioning system that constructs signal mapping by using motion data and signal fingerprints collected from built-in sensors of the smartphone. Signal fingerprint includes RSS values for the medium access

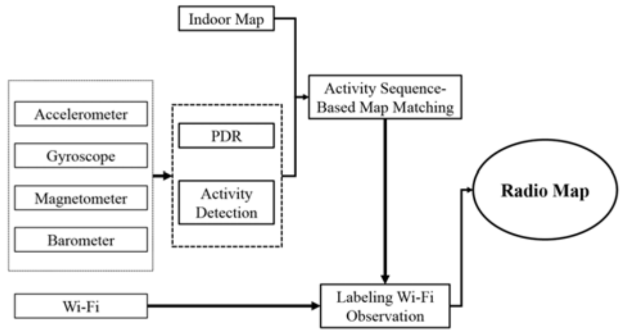


Fig. 18. Radio map construction phase.

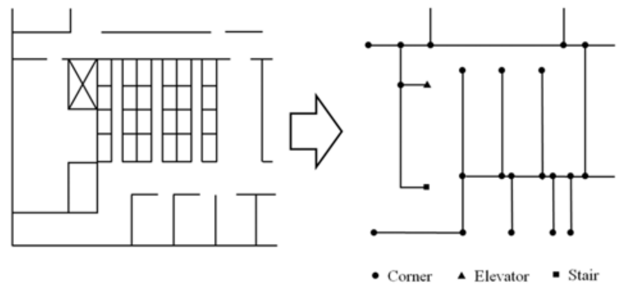


Fig. 19. Indoor map and semantic graph based on map [80].

control (MAC) address of the AP [82]. RCILS consists of the following two phases: the radio map construction and the trajectory fingerprint-based localization phase. In the first phase, the radio map is automatically constructed based on the data collected by crowdsourcing. In the second phase, RCILS performs the online localization by matching a collected RSS sequence with fingerprints in the radio map. In the radio map construction phase, as shown in Fig. 18, RCILS uses activity detection algorithms to detect user activity based on data collected by crowdsourcing and estimates the distance between two activities by using PDR algorithm. RCILS uses the indoor map as a known element and constructs a semantic graph G = (V, E), as shown in Fig. 19. Each edge e = (v1, v2) represents the trajectory between v1 and v2.

RCILS matches the trajectory with the indoor map and obtains the position of the trajectory based on the activity sequence and semantic graph of the indoor map. Subsequently, RCILS labels the signal observations based on the localization and generates a radio map with labeled signal observations. In the trajectory fingerprint-based localization phase, the RSS vector collected in the walking process constitutes a RSS sequence. The length of the sequence is determined by PDR algorithm. Based on the generated RSS sequence, RCILS performs localization by matching it with previously generated sequence-based radio map.

Various experiments were conducted in a 52.5 m $\times$ 52.5 m building to evaluate RCILS. Participants moved to accessible areas of the building with two handsets of two types of smartphones. Participants started moving from different locations for crowdsourcing. Each test was repeated ten times. Three participants used two smartphones to collect a total of 200 user trajectories for 220 minutes. The positioning error decreases when the amount of crowdsourced data increases, as shown in Fig. 20. With respect to 15 min of data, the 80$^{\text{th}}$ percentile of the localization error is approximately 21 m. For 45 min of data, the 80$^{\text{th}}$ percentile of the localization error is reduced to approximately 15 m. The localization errors significantly decreased when the amount of data increases from 15–45 min.

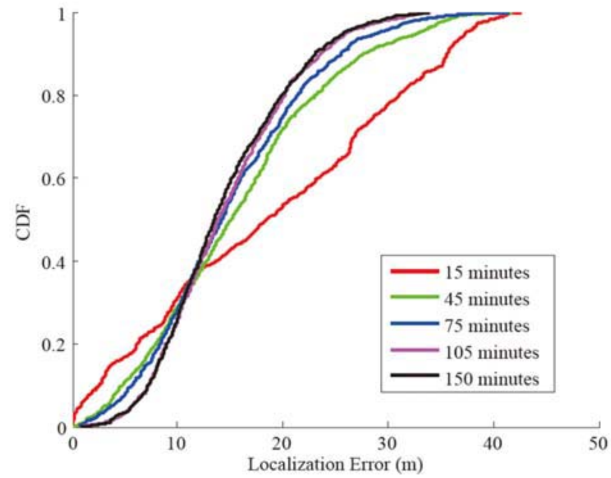


Fig. 20. Location error with incremental data [80].

RCILS displays an average error of 1.6 m in a medium-sized building. RCILS is extremely accurate because it exploits various sensor information, as well as Wi-Fi signals. However, RCILS requires an indoor map as preliminary information, and it is difficult to obtain proper localization performance during early service because it is based on crowdsourcing.

VI. Comparison of Techniques

The introduced technologies have their own characteristics, including advantages and disadvantages. We analyze these technologies with six parameters: accuracy, calculation time, versatility, robustness, security, and participation.

- Accuracy: The most important criterion in positioning technology is the accuracy [107], [108]. Specifically, the error of positioning technology indoors is misleading because the user could be in a completely different room even with a small error corresponding to only approximately 1–2 m. Therefore, the error rate of an indoor positioning technology is significantly important in the evaluation.
- Calculation time: Users use a service or application that utilizes the indoor positioning technology in the mobile device. In this case, a user should be able to quickly calculate the speed of his or her own position [109]. The performance of mobile devices is lower than that of general laptops [110]. Thus, indoor positioning technologies must perform calculations quickly in inferior computing environments.
- Versatility: Most studies report experimental results within a limited range owing to geographic area and the number of mobile devices [111], [112]. However, technologies are used in various locations such as schools,

TABLE I
ANALYSIS FOR THE REVIEWED TECHNOLOGIES

	Accuracy	Calculation Time	Versatility	Robustness	Security	Participation
GP-LVM	3.97 m error inside 600 m^2	$O(n^3)$	No	No	Yes	Not required
GraphSLAM	2.18 m error inside 600 m^2	$O(n^2)$	Yes	Yes	Yes	Not required
WiSLAM	5.4 m error inside 800 m^2	Derivate from Bayesian filter	Partially	Partially	Yes	Not required
TIX	5.4 m error inside 1020 m^2	Light algorithm	Partially	Partially	Yes	Not required
SDM	3 m error inside 598 m^2	Light algorithm	Partially	Partially	Yes	Not required
Walkie -Markie	1.65 m error inside 3600 m^2	Novel algorithm to identify Wi-Fi marks	Yes	Yes	No	Required
RCILS	3 m error inside 598 m^2	Light algorithm	Yes	Yes	No	Required

hospitals, shopping malls, and offices. Their architectures are different, and different construction may even be used in the same building. Positioning technologies must operate in variable indoor environments and not only in a limited space.

- Robustness: Robustness is an attribute that ensures that indoor positioning technologies provide location services even in unpredictable situations [113]. Examples of unpredictable situations include misbehavior of an AP or user's mobile device, and addition, change, or deletion of components within a positioning system. Specifically, in an indoor environment, this attribute is important because the aforementioned unpredictable situations are very frequent.
- Security: Indoor positioning technologies must use a user's location data. That data involves sensitive information and user privacy. Indoor positioning technologies that use this data must prevent data from flowing out. The technology must protect a server as well as application if the technology uses a server [114]–[116]. There must be no intermediary use of the data if the technology receives the user's position in real time.
- Participation: There is also a way to obtain information from the user in the method of collecting the initial data. The server collects the obtained information and improves the accuracy of the map. However, in this case, it is difficult for the server to obtain accurate information if there are few of participants to provide the information.

GP-LVM shows an error rate of 3.97 m at 600 m^2. GP-LVM also works on the client device, and it is secure. GP-LVM does not get data from users, so it does not need any participation. However, GP-LVM includes a few additional problems as well as a method to express it. GP-LVM is not extended to compute a large data set, and thus it is necessary to perform $O(n^3)$ operations for each iteration for the dimension of the state space (i.e., the number n of estimated pauses). This significantly hinders the online operations on mobile devices. Additionally, the map should be limited to a very specific shape. A fingerprint is assumed to be unique at each location and works well only in high-signal environments under these assumptions. Furthermore, if the travel record information is absent, then an arbitrary assumption is formed about the human gait pattern and data association. GP-LVM includes significant problems related to calculation time, versatility, and robustness.

GraphSLAM displays an error rate of 2.17 m at 600 m^2. GraphSLAM is designed to operate offline and inherits the advantages of GP-LVM. It ensures security and exhibits a lower error rate when compared to GP-LVM given the same area size. In contrast to GP-LXM, it does not limit the place and the versatility improves. Additionally, GraphSLAM does not need data from users, and thus it satisfies participation. However, GraphSLAM is faster than GP-LVM, although it displays $O(n^2)$ time complexity and is still too computationally intensive to be operated online on a smartphone. Therefore, it is difficult to operate GraphSLAM online. The aforementioned aspects are collectively considered, and GraphSLAM compensates for the problem of GP-LV, although it eventually presents a significant problem in terms of calculation time when used in mobile devices.

WiSLAM displays an error rate of 5.4 m at 800 m^2. WiSLAM also operates on client devices; thus, it is secure. WiSLAM does not need users' data; thus, it satisfies participation. However, it does present certain problems. Although it does not match locations, such as GP-LVM does, WiSLAM is affected by the location of the APs. Therefore, a change in the location of the AP makes it necessary to re-write the algorithm. This is a problem in terms of the robustness and calculation time. Additionally, the versatility is not perfect in this aspect.

TIX displays an error rate of 5.4 m at 1020 m^2. TIX is also operated on the client device, and thus it is also relatively safe from external attacks. Furthermore, it uses a very lightweight algorithm when compared to GP-LVM or WiSLAMl therefore, it does not linger on mobile device. Hence, TIX also satisfies the calculation time requirements. TIX does not use data from users, but rather uses RSS of APs; thus, it satisfies participation. In terms of versatility, TIX does not rely on topology, although it does not match completely because it relies on AP.

SDM displays an error rate of 3 m at 598 m^2. SDM is the same as TIX in several aspects. It has the same features and problems as TIX for all items, with the exception of accuracy. SDM displays a better accuracy rate than TIX.

Walkie-Markie displays an error rate of 1.65 m at 3600 m^2. This is the lowest error rate among the studies presented. Walkie-Markie also satisfies the versatility and robustness requirements because it does not involve any additional requirements such as an AP plan or a floor plan. Furthermore, the data is received from several users and the map is created, and thus a user can play the role of the investigator in providing information to the service or application side. However, the crowdsourcing method involves receiving from several individuals, and thus it is less secure when compared to the methods used in other studies in terms of security. Additionally, because Walkie-Markie relies heavily on users for early information gathering, early maps have a high error rate. Hence, Walkie-Markie requires time to identify Wi-Fi marks. It takes long time to calculate a map.

RCLIS displays an error rate of 4 m at 2756 m^2. Crowdsourcing produces maps with less time complexity than that created by a single individual. It is also compatible with universality because it is not restricted by location, and it is also robust to the use of other sensors as well as signals. However, it is difficult to satisfy security requirements with RCLIS because it is based on crowdsourcing. For the same reason, RCILS does not easily satisfy participation.

VII. Future Research Direction

The studied techniques should not just terminate at the research stage. It is worthwhile to use the techniques in real life. In this section, we discuss the future research directions focusing on the performance parameters, which is necessary for indoor positioning techniques to be commercially available.

The primary performance metric of indoor positioning techniques is the accuracy. So far, the researchers have improved the accuracy of indoor positioning by complementing the problems of one area of technique or by applying other areas of technology. The recent techniques improve the accuracy of indoor positioning by combining two different techniques. DeepFi [117] is the deep-learning based fingerprint indoor positioning technique with channel state information (CSI) [118]. DeepFi composes in two phases same as original fingerprint technique, the offline training phase and the online location estimation phase. DeepFi are based on the three hypotheses on CSI, different with original phases. In the offline training phase, deep learning is utilized to learn all the weights of the deep network as fingerprints. Additionally, the greedy training algorithm [119] is used to train the weights layer-by-layer to reduce complexity. In the online location estimation phase, the probabilistic method based on the radial basis function is used to obtain the estimated location [120]. Similar to DeepFi, it is possible to improve the accuracy by merging different techniques. [121]–[124] improves the accuracy of indoor positioning exploiting WiGig. WiGig is a technology that supports multi-gigabit wireless transmissions using 60 GHz license-free band [125], [126]. The 60 GHz pulse has a very short period, which is free from delay caused by multipath propagation [117]. Therefore, accurate indoor positioning is possible based on this. Various indoor positioning studies based on WiGig have been devised [121]–[124].

Calculation time is also an important parameter of the indoor positioning. When using other techniques or devices together to improve accuracy, they may follow different standards [127], [128]. It often causes the increase of the calculation time, which leads to a degradation of the overall technique. Cross-technical communication (CTC) is an important technique for directly exchanging information between heterogeneous standards. The existing works enable CTC by exploiting a side channel like frequency, amplitude or temporal modulation. However, they have limited performance under channel noise. WiZig is the CTC technique which uses modulation techniques in amplitude and time dimensions to optimize throughput for noise channels [129]. First, the theoretical model of the energy communication channel is established to understand the channel capacity. An online rate adaptation algorithm is devised to adjust the modulation strategy according to the channel condition. Subsequently, to optimize the CTC throughput, WiZig accurately controls the number of encoded energy amplitudes and the length of a receiving window based on the theoretical model. WiZig shows the achievement less than 1% symbol error rate in the real environment.

Most techniques show a low error rate in evaluation step. However, some results limit the shape or type of measurement environment in advance. These constraints prevent techniques from being used universally, which means that it doesn't have versatility and robustness. Therefore, researchers study general-purpose techniques that can be tracked without the limitation of location. The evaluation is not fixed in one place, but a place with different size and structure is used because of this reason. SemanticSLAM is a good example of such techniques [130]. SemanticSLAM is an indoor positioning technique that performs positioning with SLAM algorithm through two types of landmarks. SemanticSLAM selects the landmarks in an indoor environment with the transmitted data, which is measured by the user's device by inner sensors, such as gyros and accelerometers. Landmarks are classified into two types. One type is fixed landmark, which is determined by the structure of building measured from the inner sensor of the user device. Fixed landmarks do not vary according to the user. The other one is fluctuating landmark, which is determined according to the indoor wireless signal measured from the user device. Fluctuating landmarks may vary from user to user since the measurements vary from mobile device to mobile device. After the landmarks are defined, SemanticSLAM calculates SLAM algorithm with landmarks. SemanticSLAM conducts indoor positioning with landmarks which is based on user's device, it is not affected by the structure or type of the building.

Indoor positioning techniques must use the location information of users, which is an important privacy [131]. Thus, security is the one of the important requirements of indoor location tracking techniques. There are many privacy models to protect user's location information from the external attacks like k-anonymity [132]–[134], t-closeness [135], [136], and l-diversity [137], [138]. Recently, a technique called randomized aggregatable privacy-preserving ordinal response (RAPPOR) has attracted attention. RAPPOR is the privacy model that makes user's information confidential and makes it available data [139], [140]. The RAPPOR algorithm consists of four steps with the user's actual location values and parameters. They are performed in local, and generated data is sent to the server. First, the position data is hashed in Bloom filter B [141]. Further, we pass the i^{th} bit of B in the special equation as a random response with parameter f which is a designation parameter that controls the level of the privacy. After the equation, position data in the i^{th} bit of B is converted into new value that is identified as $B^{'}$. With the i^{th} data of S, which is a set of $B^{'}$, is set as 1 or 0 according to the probability. The resulting P, the set of result 1 and 0, is sent to the server. Other techniques, such as K-anonymity, can generate data using the original data to identify the data, but in the case of RAPPOR, it is impossible to identify the data because it is generated through two hashes.

Even if any localization technique is accurate and computationally fast, if it causes the high energy consumption of the mobile device, it cannot be used for a long time [142]. A representative example is GPS. GPS has the highest accuracy and reliability of outdoor tracking systems. However, in proportion to this, the energy consumption of GPS is very high. Rate-adaptive positioning system (RAPS) has been studied to effectively utilize GPS with efficiently consuming energy [143]. RAPS cleverly determine when to turn on GPS using a collection of techniques. In detail, RAPS use the location-time history of the user to estimate user's speed and only turns on GPS appropriately if the uncertainty of the estimated location exceeds the accuracy threshold. Further, RAPS estimate movement of user with duty-cycled accelerometer [144] and use Bluetooth communication to reduce position uncertainty among neighboring devices. Finally, RAPS detect GPS where we cannot use GPS with cell tower-RSS blacklisting and doesn't turn GPS on in these cases. When using RAPS, the lifetime of mobile devices area increased 3.8 times as compared to that when GPS was turned on continuously. It is necessary to consider how to manage energy consumption efficiently when indoor positioning techniques are practically used.

Data made from indoor positioning system which satisfies the above properties can be applied in various place. For example, indoor localization data can be used for wireless radio frequency (RF) energy transport with 60 GHz for wireless industrial sensor networks [145]–[147]. Wireless RF energy transport is the effective way to power small wireless sensors in wireless industrial sensor networks (WISN) [148]. The sensors receive energy from the device called to the sink node, which equipped with a horn antenna. However, when the sensor is located behind the obstacle, the transfer of energy becomes difficult. The solution to this problem is to use reflective beamforming [149]. A sink node reflects the signal to an element such as a ceiling and sends it to the sensors. This creates a line of sight path between the sink node and the sensor, by passing obstacles. In here, localization data use for radio beamforming. We use the positioning system to locate the sensor in detail and install an appropriate reflector antenna. This allows more efficient energy transfer. One more example is that we can use indoor localization data for rescue or evacuation in the emergency [150]–[152]. Indoor positioning acts an important role in Emergency Rescue Evacuation Support System (ERESS) [153] by locating individuals inside the building and guiding people to a safer place. In addition, when ERESS is used to evacuate, the infrastructure indoor can be broken due to disaster. Because of this reason, the fingerprint technique is not expected to achieve the accuracy in emergency situations. When designing indoor positioning system, we need to consider reducing the excessive dependence of indoor infrastructure.

VIII. CONCLUSION

As the number of mobile device have increased, various services and applications in mobile devices, based on a user's location, are becoming prevalent. The importance of positioning technology that accurately captures the current location of a user is well emphasized. The fingerprint-based wireless indoor positioning approach is widely used; however, its prerequisite step, the offline fingerprinting map must be updated or re-created frequently. Therefore, it consumes considerable amount of time and efforts. In this study, we survey the recent developments of indoor positioning techniques without an offline fingerprinting map. We classify them into three categories: SLAM, inter/extrapolation, and crowdsourcing-based technologies. We present their algorithms and characteristics, including advantages and disadvantages. We compare them in terms of our own parameters: accuracy, calculation time, versatility, robustness, security, and participation. The SLAM series techniques are good in terms of accuracy, security, and participation, but inefficient in terms of calculation time, versatility, and robustness. The inter/extrapolation techniques are good in terms of calculation time, security and participation, but inefficient in terms of accuracy, versatility, and robustness. The crowdsourcing-based technologies are good in terms of accuracy, calculation time, versatility, and robustness, but inefficient in terms of security and participation. Finally, we present the future research direction of the indoor positioning techniques. We believe that this study provides a useful perspective and necessary information for recent indoor localization technologies without offline fingerprinting map construction.

REFERENCES

[1] D. Madigan *et al.*, "Bayesian indoor positioning systems," in *Proc. INFOCOM*, vol. 2. Miami, FL, USA, 2005, pp. 1217–1227.

[2] G. Ding, Z. Tan, J. Wu, and J. Zhang, "Efficient indoor fingerprinting localization technique using regional propagation model," *IEICE Trans. Commun.*, vol. 97, no. 8, pp. 1728–1741, 2014.

[3] K. Pahlavan, X. Li, and J.-P. Makela, "Indoor geolocation science and technology," *IEEE Commun. Mag.*, vol. 40, no. 2, pp. 112–118, Feb. 2002.

[4] K. Muthukrishnan, M. Lijding, and P. Havinga, "Towards smart surroundings: Enabling techniques and technologies for localization," in *Proc. LoCA*, 2005, pp. 350–362.

[5] J. Hightower and G. Borriello, "Location systems for ubiquitous computing," *Computer*, vol. 34, no. 8, pp. 57–66, Aug. 2001.

[6] A. Haeberlen *et al.*, "Practical robust localization over large-scale 802.11 wireless networks," in *Proc. MobiCom*, Philadelphia, PA, USA, 2004, pp. 70–84.

[7] M. Vossiek *et al.*, "Wireless local positioning," *IEEE Microw. Mag.*, vol. 4, no. 4, pp. 77–86, Dec. 2003.

[8] K. Kaemarungsi and P. Krishnamurthy, "Modeling of indoor positioning systems based on location fingerprinting," in *Proc. IEEE INFOCOM*, vol. 2, 2004, pp. 1012–1022.

[9] P. Mirowski, T. K. Ho, S. Yi, and M. MacDonald, "SignalSLAM: Simultaneous localization and mapping with mixed WiFi, Bluetooth, LTE and magnetic signals," in *Proc. IPIN*, 2013, pp. 1–10.

[10] J. Liu, R. Chen, L. Pei, R. Guinness, and H. Kuusniemi, "A hybrid smartphone indoor positioning solution for mobile LBS," *Sensors*, vol. 12, no. 12, pp. 17208–17233, 2012.

[11] Y. Gu, A. Lo, and I. Niemegeers, "A survey of indoor positioning systems for wireless personal networks," *IEEE Commun. Surveys Tuts.*, vol. 11, no. 1, pp. 13–32, 1st Quart., 2009.

[12] B. Hofmann-Wellenhof, H. Lichtenegger, and J. Collins, *GPS Theory and Practice*. New York, NY, USA: Springer, 2001.

[13] D. Wells *et al.*, *Guide to GPS Positioning*. Fredericton, NB, Canada: Can. GPS Assoc., 1987.

[14] G. Dedes and A. G. Dempster, "Indoor GPS positioning—Challenges and opportunities," in *Proc. VTC-Fall*, vol. 1. Dallas, TX, USA, 2005, pp. 412–415.

[15] K. Choi, A. Bilich, K. M. Larson, and P. Axelrad, "Modified sidereal filtering: Implications for high-rate GPS positioning," *Geophys. Res. Lett.*, vol. 31, no. 22, 2004, Art. no. L22608.

[16] E. Martin, O. Vinyals, G. Friedland, and R. Bajcsy, "Precise indoor localization using smart phones," in *Proc. ACM Multimedia Conf. (MM)*, Florence, Italy, 2010, pp. 787–790.

[17] G. M. Djuknic and R. E. Richton, "Geolocation and assisted GPS," *Computer*, vol. 34, no. 2, pp. 123–125, Feb. 2001.

[18] K. Chintalapudi, A. P. Iyer, and V. N. Padmanabhan, "Indoor localization without the pain," in *Proc. MobiCom/MobiHoc*, Chicago, IL, USA, 2010, pp. 173–184.

[19] H. Liu, H. Darabi, P. Banerjee, and J. Liu, "Survey of wireless indoor positioning techniques and systems," *IEEE Trans. Syst. Man. Cybern. C, Appl. Rev.*, vol. 37, no. 6, pp. 1067–1080, Nov. 2007.

[20] S. Yoon, K. Lee, Y. Yun, and I. Rhee, "ACMI: FM-based indoor localization via autonomous fingerprinting," *IEEE Trans. Mobile Comput.*, vol. 15, no. 6, pp. 1318–1332, Jun. 2016.

[21] Y. Wang, X. Jia, H. K. Lee, and G. Y. Li, "An indoors wireless positioning system based on wireless local area network infrastructure," in *Proc. SatNav*, vol. 54, Melbourne VIC, Australia, 2003, pp. 5–11.

[22] T. Kitasuka, K. Hisazumi, T. Nakanishi, and A. Fukuda, "WiPS: Location and motion sensing technique of IEEE 802.11 devices," in *Proc. ICITA*, vol. 2. Sydney, NSW, Australia, 2005, pp. 346–349.

[23] M. Cypriani, F. Lassabe, P. Canalda, and F. Spies, "Open wireless positioning system: A Wi-Fi-based indoor positioning system," in *Proc. 70th IEEE VTC-Fall*, Anchorage, AK, USA, 2009, pp. 1–5.

[24] B. Jang and M. L. Sichitiu, "IEEE 802.11 saturation throughput analysis in the presence of hidden terminals," *IEEE/ACM Trans. Netw.*, vol. 20, no. 2, pp. 557–570, Apr. 2012.

[25] S. Feldmann, K. Kyamakya, A. Zapater, and Z. Lue, "An indoor Bluetooth-based positioning system: Concept, implementation and experimental evaluation," in *Proc. ICWN*, vol. 272. Las Vegas, NV, USA, 2003, pp. 109–113.

[26] P. Prasithsangaree, P. Krishnamurthy, and P. K. Chrysanthis, "On indoor position location with wireless LANs," in *Proc. PIMRC*, 2002, pp. 720–724.

[27] A. Bekkelien, M. Deriaz, and S. Marchand-Maillet, "Bluetooth indoor positioning," M.C.S. thesis, Dept. Comput. Sci., Univ. Geneva, Geneva, Switzerland, 2012.

[28] L. Pei *et al.*, "Using inquiry-based Bluetooth RSSI probability distributions for indoor positioning," *J. Glob. Position. Syst.*, vol. 9, no. 2, pp. 122–130, 2010.

[29] D. Focken and R. Stiefelhagen, "Towards vision-based 3-D people tracking in a smart room," in *Proc. ICMI*, Pittsburgh, PA, USA, 2002, p. 400.

[30] J. Krumm *et al.*, "Multi-camera multi-person tracking for EasyLiving," in *Proc. 3rd IEEE Int. Workshop*, Dublin, Ireland, 2000, pp. 3–10.

[31] K. Kaemarungsi and P. Krishnamurthy, "Properties of indoor received signal strength for WLAN location fingerprinting," in *Proc. MOBIQUITOUS*, Boston, MA, USA, 2004, pp. 14–23.

[32] B. Li, T. Gallagher, A. G. Dempster, and C. Rizos, "How feasible is the use of magnetic field alone for indoor positioning?" in *Proc. IPIN*, Sydney, NSW, Australia, 2012, pp. 1–9.

[33] B. Zhou, Q. Li, Q. Mao, W. Tu, and X. Zhang, "Activity sequence-based indoor pedestrian localization using smartphones," *IEEE Trans. Human–Mach. Syst.*, vol. 45, no. 5, pp. 562–574, Oct. 2015.

[34] J. Shang, X. Hu, W. Cheng, and H. Fan, "GridiLoc: A backtracking grid filter for fusing the grid model with PDR using smartphone sensors," *Sensors*, vol. 16, no. 12, p. 2137, 2016.

[35] M. A. Stelios, A. D. Nick, M. T. Effie, K. M. Dimitris, and S. C. Thomopoulos, "An indoor localization platform for ambient assisted living using UWB," in *Proc. MoMM*, Linz, Austria, 2008, pp. 178–182.

[36] A. Bekkali, H. Sanson, and M. Matsumoto, "RFID indoor positioning based on probabilistic RFID map and Kalman filtering," in *Proc. WiMOB*, White Plains, NY, USA, 2007, p. 21.

[37] Z. Sun *et al.*, "PANDAA: Physical arrangement detection of networked devices through ambient-sound awareness," in *Proc. UBICOMP*, Pittsburgh, PA, USA, 2011, pp. 425–434.

[38] W. Huang *et al.*, "Shake and walk: Acoustic direction finding and fine-grained indoor localization using smartphones," in *Proc. INFOCOM*, Toronto, ON, Canada, 2014, pp. 370–378.

[39] Y.-S. Kuo, P. Pannuto, K.-J. Hsiao, and P. Dutta, "Luxapose: Indoor positioning with mobile phones and visible light," in *Proc. MobiCom*, New York, NY, USA, 2014, pp. 447–458.

[40] B. Zhu, J. Cheng, Y. Wang, J. Yan, and J. Wang, "Three-dimensional VLC positioning based on angle difference of arrival with arbitrary tilting angle of receiver," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 1, pp. 8–22, Jan. 2018.

[41] H. Steendam, "A 3-D positioning algorithm for AOA-based VLP with an aperture-based receiver," *IEEE J. Sel. Areas Commun.*, vol. 36, no. 1, pp. 23–33, Jan. 2018.

[42] Z. Yang, Z. Wang, J. Zhang, C. Huang, and Q. Zhang, "Wearables can afford: Light-weight indoor positioning with visible light," in *Proc. MobiSys*, New York, NY, USA, 2015, pp. 317–330.

[43] S. Beauregard and M. Klepal, "Indoor PDR performance enhancement using minimal map information and particle filters," in *Proc. IEEE/ION Position Location Navig. Symp.*, 2008, pp. 141–147.

[44] F. Gustafsson and F. Gunnarsson, "Positioning using time-difference of arrival measurements," in *Proc. ICASSP*, Hong Kong, 2003, pp. 553–556.

[45] L. W. Fullerton, J. L. Richards, and I. A. Cowie, "System and method for position determination by impulse radio using round trip time-of-flight," U.S. Patent 6 611 234, Aug. 26, 2003.

[46] Y.-T. Chan, W.-Y. Tsui, H.-C. So, and P. Ching, "Time-of-arrival based localization under NLOS conditions," *IEEE Trans. Veh. Technol.*, vol. 55, no. 1, pp. 17–24, Jan. 2006.

[47] J. Yang and Y. Chen, "Indoor localization using improved RSS-based lateration methods," in *Proc. GLOBECOM*, Honolulu, HI, USA, 2009, pp. 1–6.

[48] M. Scherhaufl *et al.*, "Indoor localization of passive UHF RFID tags based on phase-of-arrival evaluation," *IEEE Trans. Microw. Theory Techn.*, vol. 61, no. 12, pp. 4724–4729, Dec. 2013.

[49] P. Bahl and V. N. Padmanabhan, "RADAR: An in-building RF-based user location and tracking system," in *Proc. INFOCOM*, vol. 2. Tel Aviv, Israel, 2000, pp. 775–784.

[50] L. M. Ni, Y. Liu, Y. C. Lau, and A. P. Patil, "LANDMARC: Indoor location sensing using active RFID," in *Proc. PerCom*, Fort Worth, TX, USA, 2003, pp. 407–415.
[51] N. Swangmuang and P. Krishnamurthy, "Location fingerprint analyses toward efficient indoor positioning," in *Proc. PerCom*, Hong Kong, 2008, pp. 100–109.
[52] M. Azizyan, I. Constandache, and R. R. Choudhury, "SurroundSense: Mobile phone localization via ambience fingerprinting," in *Proc. MobiCom*, 2009, pp. 261–272.
[53] K. Kaemarungsi, "Design of indoor positioning systems based on location fingerprinting technique," Ph.D. dissertation, School Inf. Sci., Univ. Pittsburgh, Pittsburgh, PA, USA, 2005.
[54] T.-N. Lin and P.-C. Lin, "Performance comparison of indoor positioning techniques based on location fingerprinting in wireless networks," in *Proc. WIRLES*, vol. 2, 2005, pp. 1569–1574.
[55] M. A. Al-Ammar *et al.*, "Comparative survey of indoor positioning technologies, techniques, and algorithms," in *Proc. CW*, Santander, Spain, 2014, pp. 245–252.
[56] C. Yang and H.-R. Shao, "WiFi-based indoor positioning," *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 150–157, Mar. 2015.
[57] C. Feng, W. S. A. Au, S. Valaee, and Z. Tan, "Received-signal-strength-based indoor positioning using compressive sensing," *IEEE Trans. Mobile Comput.*, vol. 11, no. 12, pp. 1983–1993, Dec. 2012.
[58] F. D. Rosa, M. Pelosi, and J. Nurmi, "Indoor positioning in WLAN," in *Mobile Positioning and Tracking: From Conventional to Cooperative Techniques*. Hoboken, NJ, USA: Wiley, 2017, pp. 261–282.
[59] L. Mainetti, L. Patrono, and I. Sergi, "A survey on indoor positioning systems," in *Proc. SoftCOM*, Split, Croatia, 2014, pp. 111–120.
[60] R. Harle, "A survey of indoor inertial positioning systems for pedestrians," *IEEE Commun. Surveys Tuts.*, vol. 15, no. 3, pp. 1281–1293, 3rd Quart., 2013.
[61] P. Torteeka and X. I. U. Chundi, "Indoor positioning based on Wi-Fi fingerprint technique using fuzzy K-nearest neighbor," in *Proc. IBCAST*, Islamabad, Pakistan, 2014, pp. 461–465.
[62] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piché, "A comparative survey of WLAN location fingerprinting methods," in *Proc. WPNC*, Hannover, Germany, 2009, pp. 243–251.
[63] S. He and S.-H. G. Chan, "Wi-Fi fingerprint-based indoor positioning: Recent advances and comparisons," *IEEE Commun. Surveys Tuts.*, vol. 18, no. 1, pp. 466–490, 1st Quart., 2016.
[64] R. Faragher and R. Harle, "Location fingerprinting with Bluetooth low energy beacons," *IEEE J. Sel. Areas Commun.*, vol. 33, no. 11, pp. 2418–2428, Nov. 2015.
[65] P. Davidson and R. Piché, "A survey of selected indoor positioning methods for smartphones," *IEEE Commun. Surveys Tuts.*, vol. 19, no. 2, pp. 1347–1370, 2nd Quart., 2017.
[66] T. Bailey and H. Durrant-Whyte, "Simultaneous localization and mapping (SLAM): Part II," *IEEE Robot. Autom. Mag.*, vol. 13, no. 3, pp. 108–117, Sep. 2006.
[67] C. Wu, Z. Yang, and Y. Liu, "Smartphones based crowdsourcing for indoor localization," *IEEE Trans. Mobile Comput.*, vol. 14, no. 2, pp. 444–457, Feb. 2015.
[68] H. Shin, Y. Chon, and H. Cha, "Unsupervised construction of an indoor floor plan using a smartphone," *IEEE Trans. Syst., Man, Cybern. C, Appl. Rev.*, vol. 42, no. 6, pp. 889–898, Nov. 2012.
[69] B. D. Ferris, D. Fox, and N. Lawrence, "WiFi-SLAM using Gaussian process latent variable models," in *Proc. IJCAI*, San Francisco, CA, USA, 2007, pp. 2480–2485.
[70] J. Huang *et al.*, "Efficient, generalized indoor WiFi GraphSLAM," in *Proc. ICRA*, Shanghai, China, 2011, pp. 1038–1043.
[71] L. Bruno and P. Robertson, "WiSLAM: Improving FootSLAM with WiFi," in *Proc. IPIN*, 2011, pp. 1–10.
[72] Y. Gwon and R. Jain, "Error characteristics and calibration-free techniques for wireless LAN-based location estimation," in *Proc. 2nd Int. Workshop Mobility Manag. Wireless Access Protocols*, 2004, pp. 2–9.
[73] H. Lim, L. -C. Kung, J. C. Hou, and H. Luo, "Zero-configuration indoor localization over IEEE 802.11 wireless infrastructure," *Wireless Netw.*, vol. 16, no. 2, pp. 405–420, 2010.
[74] D. C. Brabham, "Crowdsourcing as a model for problem solving: An introduction and cases," *Convergence*, vol. 14, no. 1, pp. 75–90, 2008.
[75] S. Yang, P. Dessai, M. Verma, and M. Gerla, "FreeLoc: Calibration-free crowdsourced indoor localization," in *Proc. INFOCOM*, Turin, Italy, 2013, pp. 2481–2489.
[76] P. Bolliger, "Redpin—Adaptive, zero-configuration indoor localization through user collaboration," in *Proc. Melt*, San Francisco, CA, USA, 2008, pp. 55–60.
[77] M. Lee, H. Yang, D. Han, and C. Yu, "Crowdsourced radiomap for room-level place recognition in urban environment," in *Proc. PERCOM*, 2010, pp. 648–653.
[78] S. Teller *et al.*, "Organic indoor location discovery," Comput. Sci. Artif. Intell. Lab., Cambridge, MA, USA, Rep. MIT-CSAIL-TR-2008-075, p. 16, 2008.
[79] J.-P. Park, D. Curtis, S. Teller, and J. Ledlie, "Implications of device diversity for organic localization," in *Proc. INFOCOM*, Shanghai, China, 2011, pp. 3182–3190.
[80] J. Ledlie *et al.*, "Molé: A scalable, user-generated WiFi positioning engine," *J. Location Based Services*, vol. 6, no. 2, pp. 55–80, 2012.
[81] G. Shen, Z. Chen, P. Zhang, T. Moscibroda, and Y. Zhang, "Walkie-Markie: Indoor pathway mapping made easy," in *Proc. USENIX*, 2013, pp. 85–98.
[82] B. Zhou, Q. Li, Q. Mao, and W. Tu, "A robust crowdsourcing-based indoor localization system," *Sensors*, vol. 17, no. 4, p. 864, 2017.
[83] E. Kaplan and C. Hegarty, *Understanding GPS: Principles and Applications*. Boston, MA, USA: Artech House, 2005.
[84] *GPS Accuracy*. Accessed: May 7, 2018. [Online]. Available: https://www.gps.gov/systems/gps/performance/accuracy/
[85] Y. Wang, X. Yang, Y. Zhao, Y. Liu, and L. Cuthbert, "Bluetooth positioning using RSSI and triangulation methods," in *Proc. CCNC*, Las Vegas, NV, USA, 2013, pp. 837–842.
[86] A. M. Ladd, K. E. Bekris, A. P. Rudys, D. S. Wallach, and L. E. Kavraki, "On the feasibility of using wireless Ethernet for indoor localization," *IEEE Trans. Robot. Autom.*, vol. 20, no. 3, pp. 555–559, Jun. 2004.
[87] G. Ding, Z. Tan, J. Wu, J. Zeng, and L. Zhang, "Indoor fingerprinting localization and tracking system using particle swarm optimization and Kalman filter," *IEICE Trans. Commun.*, vol. 98, no. 3, pp. 502–514, 2015.
[88] J. Schiller and A. Voisard, *Location-Based Services*. Amsterdam, The Netherlands: Elsevier, 2004.
[89] J. Wu, S. Guo, H. Huang, W. Liu, and Y. Xiang, "Information and communications technologies for sustainable development goals: State-of-the-art, needs and perspectives," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 3, pp. 2389–2406, 3rd Quart., 2018.
[90] J.-G. Park *et al.*, "Growing an organic indoor location system," in *Proc. MobiSys*, San Francisco, CA, USA, 2010, pp. 271–284.
[91] Z. Yang, C. Wu, and Y. Liu, "Locating in fingerprint space: wireless indoor localization with little human intervention," in *Proc. MobiCom*, Istanbul, Turkey, 2012, pp. 269–280.
[92] M. Youssef and A. Agrawala, "The Horus WLAN location determination system," in *Proc. 3rd Int. Conf. Mobile Syst. Appl. Services*, 2005, pp. 205–218
[93] C. Wu, Z. Yang, Y. Liu, and W. Xi, "WILL: Wireless indoor localization without site survey," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 4, pp. 839–848, Apr. 2013.
[94] J. N. Laneman, G. W. Wornell, and D. N. C. Tse, "An efficient protocol for realizing cooperative diversity in wireless networks," in *Proc. ISIT*, Washington, DC, USA, 2001, p. 294.
[95] H. Durrant-Whyte and T. Bailey, "Simultaneous localization and mapping: Part I," *IEEE Robot. Autom. Mag.*, vol. 13, no. 2, pp. 99–110, Jun. 2006.
[96] G. D'Agostini, "A multidimensional unfolding method based on Bayes' theorem," *Nucl. Instrum. Methods Phys. Res. A Accelerators Spectrometers Detectors Assoc. Equip.*, vol. 362, nos. 2–3, pp. 487–498, 1995.
[97] M. Hagströmer, P. Oja, and M. Sjöström, "The international physical activity questionnaire (IPAQ): A study of concurrent and construct validity," *Public Health Nutr.*, vol. 9, no. 6, pp. 755–762, 2006.
[98] M. M. Morrison, "Inertial measurement unit," U.S. Patent 4 711 125, Dec. 8, 1987.
[99] E. Foxlin, "Pedestrian tracking with shoe-mounted inertial sensors," *IEEE Comput. Graph. Appl.*, vol. 25, no. 6, pp. 38–46, Nov./Dec. 2005.
[100] P. Robertson, M. Angermann, and B. Krach, "Simultaneous localization and mapping for pedestrians using only foot-mounted inertial sensors," in *Proc. 11th Int. Conf. Ubiquitous Comput.*, 2009, pp. 93–96.
[101] P. Robertson, M. Angermann, and M. Khider, "Improving simultaneous localization and mapping for pedestrian navigation and automatic mapping of buildings by using online human-based feature labeling," in *Proc. PLANS*, Indian Wells, CA, USA, 2010, pp. 365–374.
[102] M. S. Arulampalam, S. Maskell, N. Gordon, and T. Clapp, "A tutorial on particle filters for online nonlinear/non-Gaussian–Bayesian tracking," *IEEE Trans. Signal Process.*, vol. 50, no. 2, pp. 174–188, Feb. 2002.

[103] K. P. Murphy, "Bayesian map learning in dynamic environments," in *Proc. Adv. Neural Inf. Process. Syst.*, 2000, pp. 1015–1021.

[104] K. P. Murphy, "Dynamic Bayesian networks: Representation, inference and learning," Ph.D. dissertation, Comput. Sci. Div., Univ. California at Berkeley, Berkeley, CA, USA, 2002.

[105] C. Aironet, "802.11 a/b/g wireless CardBus adapter," Data Sheet, 2012. [Online]. Available: http://www.cisco.com/c/en/us/products/collateral/wireless/aironet-802-11a-bg-cardbus-wireless-lan-clientadapter-cb21ag/productdatasheet09186a00801ebc29.html

[106] S.-J. Yu, S.-S. Jan, and D. S. De Lorenzo, "Indoor navigation using Wi-Fi fingerprinting combined with pedestrian dead reckoning," in *Proc. PLANS*, Monterey, CA, USA, 2018, pp. 246–253.

[107] S. Von Watzdorf and F. Michahelles, "Accuracy of positioning data on smartphones," in *Proc. LocWeb*, Tokyo, Japan, 2010, Art. no. 2.

[108] M.-S. Choi and B. Jang, "An accurate fingerprinting based indoor positioning algorithm," *Int. J. Appl. Eng. Res.*, vol. 12, no. 1, pp. 86–90, 2017.

[109] B. Li, J. Salter, A. G. Dempster, and C. Rizos, "Indoor positioning techniques based on wireless LAN," in *Proc. IEEE Int. Conf. LAN*, 2007, pp. 13–16.

[110] G. Huerta-Canepa and D. Lee, "A virtual cloud computing provider for mobile devices," in *Proc. MCS*, San Francisco, CA, USA, 2010, Art. no. 6.

[111] Z. Chen *et al.*, "Fusion of WiFi, smartphone sensors and landmarks using the Kalman filter for indoor localization," *Sensors*, vol. 15, no. 1, pp. 715–732, 2015.

[112] J. Wang *et al.*, "LiFS: Low human-effort, device-free localization with fine-grained subcarrier information," in *Proc. MobiCom*, New York, NY, USA, 2016, pp. 243–256.

[113] R. Casas, D. Cuartielles, A. Marco, H. J. Gracia, and J. L. Falco, "Hidden issues in deploying an indoor location system," *IEEE Pervasive Comput.*, vol. 6, no. 2, pp. 62–69, Apr./Jun. 2007.

[114] A. Smailagic and D. Kogan, "Location sensing and privacy in a context-aware computing environment," *IEEE Wireless Commun.*, vol. 9, no. 5, pp. 10–17, Oct. 2002.

[115] M. Brunato and C. K. Kallo, "Transparent location fingerprinting for wireless services," Dept. Inf. Eng. Comput. Sci., Univ. Trento, Trento, Italy, Rep. DIT-02-071, 2002.

[116] A. R. Beresford and F. Stajano, "Location privacy in pervasive computing," *IEEE Pervasive Comput.*, vol. 2, no. 1, pp. 46–55, Jan./Mar. 2003.

[117] X. Wang, L. Gao, S. Mao, and S. Pandey, "DeepFi: Deep learning for indoor fingerprinting using channel state information," in *Proc. WCNC*, New Orleans, LA, USA, 2015, pp. 1666–1671.

[118] V. Havary-Nassab, S. Shahbazpanahi, A. Grami, and Z.-Q. Luo, "Distributed beamforming for relay networks based on second-order statistics of the channel state information," *IEEE Trans. Signal Process.*, vol. 56, no. 9, pp. 4306–4316, Sep. 2008.

[119] G. E. Hinton, S. Osindero, and Y.-W. Teh, "A fast learning algorithm for deep belief nets," *Neural Comput.*, vol. 18, no. 7, pp. 1527–1554, 2006.

[120] D.-S. Huang, "Radial basis probabilistic neural networks: Model and application," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 13, no. 7, pp. 1083–1101, 1999.

[121] X. Han, J. Wang, W. Shi, Q. Niu, and L. Xu, "Indoor precise positioning algorithm using 60GHz pulse based on compressive sensing," *J. Math. Comput. Sci.*, vol. 16, no. 2, pp. 256–272, 2016.

[122] J. Wang *et al.*, "Design and simulation of high-precision position system using 60 GHz pulse," *J. Circuit. Syst. Comput.*, vol. 25, no. 8, 2016, Art. no. 1650092.

[123] A. Jafari *et al.*, "NLOS influence on 60 GHz indoor localization based on a new TDOA extraction approach," in *Proc. EuMC*, Nuremberg, Germany, 2013, pp. 330–333.

[124] T. Redant *et al.*, "20.1 A 40nm CMOS receiver for 60GHz discrete-carrier indoor localization achieving mm-precision at 4m range," in *Proc. ISSCC*, San Francisco, CA, USA, 2014, pp. 342–343.

[125] P. Smulders, "Exploiting the 60 GHz band for local wireless multimedia access: Prospects and future directions," *IEEE Commun. Mag.*, vol. 40, no. 1, pp. 140–147, Jan. 2002.

[126] H. Zhang *et al.*, "Resource allocation in spectrum-sharing OFDMA femtocells with heterogeneous services," *IEEE Trans. Commun.*, vol. 62, no. 7, pp. 2366–2377, Jul. 2014.

[127] R. Atat *et al.*, "Enabling cyber-physical communication in 5G cellular networks: Challenges, spatial spectrum sensing, and cyber-security," *IET Cyber Phys.Syst. Theory Appl.*, vol. 2, no. 1, pp. 49–54, Apr. 2017.

[128] J. An *et al.*, "Achieve sustainable ultra-dense heterogeneous networks for 5G," *arXiv preprint arXiv:1711.05044*, 2017.

[129] X. Guo, X. Zheng, and Y. He, "WiZig: Cross-technology energy communication over a noisy channel," in *Proc. INFOCOM*, Atlanta, GA, USA, 2017, pp. 1–9.

[130] H. Abdelnasser *et al.*, "SemanticSLAM: Using environment landmarks for unsupervised indoor localization," *IEEE Trans. Mobile Comput.*, vol. 15, no. 7, pp. 1770–1782, Jul. 2016.

[131] A. Konstantinidis *et al.*, "Privacy-preserving indoor localization on smartphones," in *Proc. ICDE*, Helsinki, Finland, 2016, pp. 1470–1471.

[132] L. Sweeney, "k-Anonymity: A model for protecting privacy," *Int. J. Uncertainty Fuzziness Knowl. Based Syst.*, vol. 10, no. 5, pp. 557–570, 2002.

[133] K. LeFevre, D. J. DeWitt, and R. Ramakrishnan, "Mondrian multidimensional K-anonymity," in *Proc. ICDE*, Atlanta, GA, USA, 2006, p. 25.

[134] L. Sweeney, "Achieving K-anonymity privacy protection using generalization and suppression," *Int. J. Uncertainty Fuzziness Knowl. Based Syst.*, vol. 10, no. 5, pp. 571–588, 2002.

[135] N. Li, T. Li, and S. Venkatasubramanian, "t-Closeness: Privacy beyond k-anonymity and l-diversity," in *Proc. ICDE*, Istanbul, Turkey, 2007, pp. 106–115.

[136] J. Soria-Comas, J. Domingo-Ferrer, D. Sánchez, and S. Martinez, "t-Closeness through microaggregation: Strict privacy with enhanced utility preservation," *IEEE Trans. Knowl. Data Eng.*, vol. 27, no. 11, pp. 3098–3110, Nov. 2015.

[137] Z. Tu *et al.*, "Beyond K-anonymity: Protect your trajectory from semantic attack," in *Proc. SECON*, San Diego, CA, USA, 2017, pp. 1–9.

[138] L.-P. Sondeck, M. Laurent, and V. Frey, "The semantic discrimination rate metric for privacy measurements which questions the benefit of t-closeness over l-diversity," in *Proc. SECRYPT*, vol. 6. Madrid, Spain, 2017, pp. 285–294.

[139] Ú. Erlingsson, V. Pihur, and A. Korolova, "RAPPOR: Randomized aggregatable privacy-preserving ordinal response," in *Proc. SIGSAC*, 2014, pp. 1054–1067.

[140] J. W. Kim, D.-H. Kim, and B. Jang, "Application of local differential privacy to collection of indoor positioning data," *IEEE Access*, vol. 6, pp. 4276–4286, 2018.

[141] H. Song, S. Dharmapurikar, J. Turner, and J. Lockwood, "Fast hash table lookup using extended bloom filter: An aid to network processing," in *Proc. SIGCOMM*, vol. 35. Philadelphia, PA, USA, 2005, pp. 181–192.

[142] K. Wang, Y. Wang, Y. Sun, S. Guo, and J. Wu, "Green industrial Internet of Things architecture: An energy-efficient perspective," *IEEE Commun. Mag.*, vol. 54, no. 12, pp. 48–54, Dec. 2016.

[143] J. Paek, J. Kim, and R. Govindan, "Energy-efficient rate-adaptive GPS-based positioning for smartphones," in *Proc. MobiSys*, San Francisco, CA, USA, 2010, pp. 299–314.

[144] S. Bosch, R. Marin-Perianu, P. Havinga, and M. Marin-Perianu, "Energy-efficient assessment of physical activity level using duty-cycled accelerometer data," *Procedia Comput. Sci.*, vol. 5, pp. 328–335, 2011.

[145] H. Li, K. Ota, M. Dong, and H.-H. Chen, "Efficient energy transport in 60 GHz for wireless industrial sensor networks," *IEEE Wireless Commun.*, vol. 24, no. 5, pp. 143–149, Oct. 2017.

[146] B. Jang, J. B. Lim, and M. L. Sichitiu, "An asynchronous scheduled MAC protocol for wireless sensor networks," *Comput. Netw.*, vol. 57, no. 1, pp. 85–98, 2013.

[147] J. B. Lim, B. Jang, and M. L. Sichitiu, "MCAS-MAC: A multichannel asynchronous scheduled MAC protocol for wireless sensor networks," *Comput. Commun.*, vol. 56, pp. 98–107, Feb. 2015.

[148] V. C. Gungor and G. P. Hancke, "Industrial wireless sensor networks: Challenges, design principles, and technical approaches," *IEEE Trans. Ind. Electron.*, vol. 56, no. 10, pp. 4258–4265, Oct. 2009.

[149] T. A. Vu *et al.*, "UWB Vivaldi antenna for impulse radio beamforming," in *Proc. NORCHIP*, Trondheim, Norway, 2009, pp. 1–5.

[150] Y. Inoue, A. Sashima, T. Ikeda, and K. Kurumatani, "Indoor emergency evacuation service on autonomous navigation system using mobile phone," in *Proc. ISUC*, Osaka, Japan, 2008, pp. 79–85.

[151] P.-H. Chen and F. Feng, "A fast flow control algorithm for real-time emergency evacuation in large indoor areas," *Fire Safety J.*, vol. 44, no. 5, pp. 732–740, 2009.

[152] Y. Chen, L. Sun, F. Wang, and X. Zhou, "Congestion-aware indoor emergency navigation algorithm for wireless sensor networks," in *Proc. GLOBECOM*, Kathmandu, Nepal, 2011, pp. 1–5.

[153] Y. Hayakawa *et al.*, "Development of emergency rescue evacuation support system in panic-type disasters," in *Proc. CCNC*, Las Vegas, NV, USA, 2012, pp. 52–53.

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