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A survey of calibration-free indoor positioning systems

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ABSTRACT

Last decade observed a significant research effort directed towards indoor localization utilizing location fingerprinting techniques. Fingerprinting solutions generally require a pre-deployment site survey procedure during which a radio-map is constructed by laboriously collecting signal strength samples (e.g., Wi-Fi) over the whole localization area. However, such localization efforts have certain shortcomings. For example, it is time consuming, labor intensive, vulnerable to environmental changes, and the process requires certain pedigree on the surveyor that may deem the fingerprinting techniques impractical to be deployed over large areas (e.g., shopping malls, multi-storey offices/residences, etc.). Newer emerging techniques try to bypass this *expensive* pre-deployment effort of fingerprinting solutions altogether. They may build the radio-map through the *implicit* participation of the building occupants, office employee, shoppers, visitors, etc. Apart from the traditional performance comparison criteria like accuracy, precision, robustness, scalability, algorithmic complexity based on which the localization techniques were evaluated, these newer approaches warrant some additional ones. For example, whether they require an actual geographical map of the localization area, the percentage of occasional location fix to ensure reasonable accuracy, the usage of explicit/implicit user participation to construct the radio map, the usage of building landmarks (e.g., entrance, conference room, elevator, escalator, etc.) or additional sensors (e.g., accelerometer, gyroscope, compass, etc.), whether they address device heterogeneity, etc. In this article, we survey the newer emerging fingerprinting solutions that try to relieve the pre-deployment woes. We also identify some newer performance comparison criteria based on these solutions' inherent characteristics, and apply them together with the traditional ones in order to evaluate a number of such proposed systems.

1. Introduction

Accurate real-time indoor location determination is an indispensable part to enable various context-aware services and protocols [1–3]. Its applications range from a hospital's inventory and medical resource tracking, navigation tools for fire-fighters inside an unknown indoor environment, to various commercial location-based services (e.g., finding the cheapest store, sales, or electronic coupons inside a shopping mall, etc.). While Global Positioning System (GPS) is the most popular outdoor localization system, it has certain limitations when applied inside the indoor environment. Indoor environment requires finer granularity and precision of localization accuracy. For example, while a 5–10 m accuracy may well be quite acceptable outdoor, when inside a building, the target could be in different rooms. From operational perspective, GPS's signals are not designed to penetrate most construction materials, and generally require line-of-sight (LOS) transmission between receivers and satellites.

An indoor positioning system (IPS) is a framework consisting of a network of devices (both customized or off-the-shelf) that are used to wirelessly locate objects or people carrying handheld devices inside a building. The research efforts for such systems over the years can largely be divided into two main categories:

- Those that rely on specialized hardware (e.g., IR or RF tags, ultrasound receiver, etc.) and require extensive deployment of infrastructure throughout the service area solely for localization purpose [4–7]. They may also require customized tags attached to an object or specialized client devices to be carried by the person to be tracked.
- Those that are built on top of existing infrastructure (e.g., Wi-Fi or Bluetooth communication networks) and use off-the-shelf wireless networking hardware found in handheld devices.

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The family of various location fingerprinting [8–13] or model based [8] techniques where RSS measurement is used to estimate the distance between a transmitter and a receiver based on some radio propagation model, and other proximity based approaches [14–19] found in wireless sensor networks fall into the second category above. Location fingerprinting techniques hold more potential in an IPS because they offer finer accuracy (≈2–3 m) and precision compared to both the model based or proximity based approaches. However, it is much lower than many of the infrastructure-based scheme's cm-level accuracy. There is currently no de facto standard for an IPS design. Nevertheless, there are several commercial systems in the market. Firefly [20] (IR), OPTOTRAK [21] (Camera + IR), Sonitor [22] (Ultrasound) are client-tag based infrastructure oriented systems that require extensive deployment effort. Ubisense [23] (UWB), Topaz [24] (Bluetooth), Apple's iBeacon [25] (Bluetooth Low Power), MotionStar [26] (Magnetic), Easy Living [27] (Camera) are a few other commercial systems that require infrastructure support. Among the fingerprinting class, there are Ekahau [28] and GiPStech [29] which operate by building the Wi-Fi and magnetic fingerprints' map over the localization area, respectively.

In this article, we mainly concentrate on the fingerprinting techniques because of their promise towards solving the localization problem *inexpensively*. We first provide an overview of the traditional fingerprinting research, and its drawbacks. Then we point out the current research trends which try to address and resolve these shortcomings. Fingerprinting solutions generally require a pre-deployment site survey procedure during which a radio-map is constructed by laboriously collecting signal strength samples (e.g., Wi-Fi) over the whole localization area. However, such localization efforts have certain shortcomings. For example, it is time consuming, labor intensive, vulnerable to environmental changes, and the process requires certain pedigree on the part of the surveyor that may deem the fingerprinting techniques impractical to be deployed over large areas (e.g., shopping malls, multi-storey offices/residences, etc.).

There is a breed of newer emerging calibration-free techniques that try to relieve the pre-deployment woes of the fingerprinting solutions discussed above. In this article, we provide a survey of such calibration-free systems. We also identify some newer performance comparison criteria based on these solutions' inherent characteristics, and apply them together with the traditional ones in order to evaluate a number of such proposed systems. Our main target is to provide a qualitative overview of such systems, and offer a quantitative comparison among them whenever possible. To the best of our knowledge, our article is the first to provide such a survey of the calibration-free indoor localization techniques, which will become increasingly important.

The survey paper is organized as follows. We explain the basic fingerprinting approach in detail, and its apparent shortcomings in Section 2. In Section 3, we outline both the traditional and newer performance comparison criteria that we identify, considering the inherent characteristics of the emerging approaches that try to get rid of the pre-deployment woes typically seen in the fingerprinting based solutions. Next, we discuss a few emerging calibration-free techniques in Section 4, and provide a qualitative comparison of the systems in Section 5. Finally, we conclude in Section 6 by pointing out some of the future research directions.

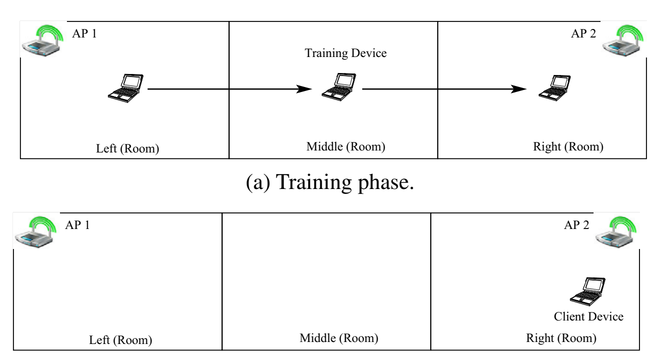
2. Location fingerprinting techniques

Over the past decade, there had been a growing interest in indoor localization techniques that rely on in-building communications infrastructure (e.g., Wi-Fi, Bluetooth, etc.) mainly because it allows the design of an easily deployable low-cost positioning system. RADAR [8] opened the door to utilize Wi-Fi communications infrastructure widely ubiquitous in the residential or commercial buildings by using location fingerprinting techniques. Even though these fingerprinting techniques offer coarser accuracy and precision compared to its infrastructure based counterparts (e.g., ActiveBAT [5], Cricket [6], etc.), its advantage lies in using the existing infrastructure and off-the-shelf hardware in providing the positioning service. Subsequently, a lot of similar research followed suit in order to achieve finer accuracy and precision, but at the same time retaining the inherent benefits of such techniques.

Most of these approaches utilize location fingerprinting techniques [8,10,9,28], that makes use of the already available infrastructure but entail a laborious training phase in order to construct the radio-map. Fingerprinting based systems generally have two phases – offline training phase and online location estimation phase. During the offline phase, the location fingerprints (i.e., signal strength samples) at the selected locations of interest are collected, yielding the so-called radio map. During the online location estimation phase, the signal strength samples (e.g., received signal strength (RSS) perceived at the access points (APs) from the client device, or vice versa, will be sent to a positioning engine. This engine will then *compare* the observed fingerprint with the previously collected radio-map, and will return the corresponding location with which the fingerprint produces the best match. A simplistic diagram explaining the fingerprinting technique is shown in Fig. 1. After conducting the site survey inside the space of interest (i.e., the three rooms) of Fig. 1, its radio map may look like:

During the online phase of Fig. 1b, if the client device perceives RSSs −92 and −51 dBm from AP 1 and 2, respectively, then its location can be resolved as the "Right" room since it has the closet match (see the radio map of Table 1). This is the main operating principle of the fingerprinting based solutions. Generally, pattern matching techniques are utilized for fingerprinting based localization algorithms. For example, Nearest Neighbor (NN) is used for the above example, and its variants *k*NN and weighted *k*NN have been utilized in [8,30], respectively. Among other algorithms, the probabilistic Maximum Likelihood Estimator (MLE) [9–11,30–32] is quite popular, while factor graphs [33], kernel estimation [34,35], neural network [36,37], support vector machine (SVM) [30,38], and extreme learning machine [39] have been applied as well.

The fingerprint's representation has also attracted significant attention as well. From the simple average RSS [8] which has been used in our example in Table 1, to Gaussian model [32,40] or other complex distributions [10,41], and even histogram representation [11,13] of RSS at a particular location – all have been investigated. Moreover, because of RSS's variability among different client devices under the same wireless condition, other fingerprints like SSD [42], HLF [43], DIFF [44], ordered sequence of RSSs [19] have also emerged.



(a) Training phase.

(b) Location estimation phase.

Fig. 1. Schematic diagram of location fingerprinting technique inside a 3 room space of interest with 2 APs.

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Table 1
An example radio map for the scenario of Fig. 1.

Location	RSS (in dBm)	
	AP 1	AP 2
Left (Room)	−50	−90
Middle (Room)	−70	−70
Right (Room)	−90	−50

Based on the operating principle of a fingerprinting technique, its training phase calibration of radio map comes with various challenges, e.g.,

- It is time consuming, labor intensive, and vulnerable to environmental changes. The process also requires certain pedigree on the part of the surveyor.
- The accuracy and precision offered by existing fingerprinting solutions need to be robust in the face of unforeseen environmental circumstances. For example, an average localization error of 2–3 m may locate a user on either side of a dividing wall depending on the time or its surroundings. Therefore, apart from achieving reasonable localization error, a 100% room-level accuracy is also desired for indoor environment at all times or settings.
- An implicit assumption of similar wireless conditions is held during both the training and online location estimation phases (even in our example in Fig. 1), which may not hold in real scenarios due to movement of furniture, adding or deleting of APs, density of crowds and the associated interference caused by their devices, etc. Therefore, an online update phase is necessary to reflect the real settings into the training radio-map database.
- The labor intensive training phase may not be scalable inside big buildings or commercial indoor environment.
- Finally, device heterogeneity has been observed to cause significant anomalies in some fingerprints (especially RSS) across different client devices even under the same wireless conditions [32,42–45]. Since a positioning system cannot assume that its users carry the same device with which the training phase has been carried out, this issue needs to be addressed as well.

A newer solution is thus required that is free from the aforementioned drawbacks. Consequently, seeking a calibration-free system has become the recent research trend among fingerprinting based techniques that retain the advantage of using existing infrastructure and off-the-shelf hardware.

3. Performance comparison criteria

In this section, we introduce the performance comparison criteria in order to evaluate the various calibration free IPSs found in the literature. These performance comparison properties have largely been divided into two main categories, namely the traditional ones, and the calibration-free ones. Apart from the traditional performance comparison criteria like accuracy, precision, robustness, scalability, cost, complexity, and latency, based on which the localization techniques were evaluated, the newer approaches warrant some additional ones. For example, whether they require an actual geographical map of the localization area, the percentage of occasional location fix needed to ensure reasonable accuracy, the need for explicit/implicit user participation to construct the radio map, the usage of building landmarks (e.g., assumption of knowledge of some known locations) or additional sensors (e.g., accelerometer, gyroscope, compass, etc.), whether they address device heterogeneity, etc. These comparison criteria are quite important in evaluating the calibration-free newer techniques since the traditional ones alone cannot completely characterize the approaches' performances. In the following, we elaborately discuss both types of performance comparison criteria.

3.1. Traditional performance comparison criteria

3.1.1. Accuracy and precision

Accuracy (or localization error) and precision are the two most important performance metrics of a positioning system. Localization error is generally defined as the Euclidean distance between the actual and estimated location [1,2,46,47]. While accuracy is represented by a numeric value, precision gives a measure how consistently the accuracy can be achieved. Cumulative distribution function (CDF) [48,49,42] is usually utilized to show the overall performance of a positioning system. For example, a median of 3 m in the CDF graph indicates that 50% of the occasions, the system's localization error (or accuracy) is within 3 m.

3.1.2. Scalability

In general, a positioning system needs to scale w.r.t. two parameters: (i) geography and (ii) density. Most works in the literature report their experimental results within a limited scope both in terms of geographical area, and the number of mobile devices [1]. A system will be termed as scalable only when it is able to perform the same when deployed inside a large testbed offering its service to a lot of client devices as it may have been shown to perform in its limited scope.

3.1.3. Robustness

Robustness is the property that ensures the positioning system to offer location services in the face of unforeseen circumstances, e.g., malfunctioning of APs or mobile devices, surrounding changes, inclusion or exclusion of newer components inside the positioning system (e.g., shutdown of an active AP), etc. [47]. In other words, the positioning system should still be operative, however, it may provide coarser accuracy compared to the previous ideal scenario.

3.1.4. Security and privacy

A secure positioning system is not vulnerable to attacks from adversaries, and privacy ensures the confidentiality of location data [1,47]. As indicated in [50], security and privacy can be maintained from the system architecture side, while a client-based positioning system (i.e., the client software computes its own location) can also easily ensure privacy of location data [51].

3.1.5. Cost and complexity

The infrastructure based positioning systems require complex and expensive sensors or transceivers to be installed over the whole localization area [4–6]. The fingerprinting solutions are generally cost-effective because they reuse the existing communication infrastructure such as WLAN [9,8,10,28]. However, they may require professional engineers to carry out the training phase to build the radio-map. Another aspect of complexity is the running time of the positioning algorithm. A computationally fast and feasible algorithm will be more attractive to serve many location queries from the clients simultaneously. This is important for client based positioning system as well where the client computes its own location because of its limited processing and battery capability.

3.1.6. Technology

The technology upon which the positioning algorithm is designed plays an important role in the system's widespread availability or deployability. For example, a WLAN (e.g., RADAR [8], Horus [10], Ekahau [28], etc.) or Bluetooth (e.g., [52,42]) based system is more attractive from commissioning purpose. This is because they can be tested easily, the positioning service can be made available to a greater user-base, and overall the system could be deployed seamlessly utilizing the already existing infrastructure. On the contrary, IR [4], Ultrasound [22], UWB [23,53], Audible sound [54], Camera [27] generally require some degree of infrastructure to be setup over the localization area, and customized badges/sensors to be worn by the personnel to be located, which ultimately might make their deployment less attractive. Many systems even try to combine two or three technologies together to build a hybrid positioning system, thereby merging their advantages. For example, Radianse [55] uses RFID + Wi-Fi, Active BAT [5], Cricket [6] and HP Lab's Smart-LOCUS [56] use RF + ultrasound signals, Place Lab [57] and Skyhook [58] use GPS + GSM + Wi-Fi, SurroundSense [59] utilizes ambient features such as acceleration, sound, light, color together with Wi-Fi signals, etc. The enhanced localization solution (ELS) [60] uses inertial sensors integrated inside smartphone and applies human mobility modelling (HMM), and machine learning techniques. It falls back to using standard location tracking techniques (e.g., GPS + GSM + Wi-Fi) only when the HMM and machine learning approach fails to provide location information.

3.1.7. Latency

Latency generally quantifies the responsiveness of an IPS. The faster an IPS can provide a user with location information, the better is the responsiveness of the system. For example, an inquiry based Bluetooth IPS introduced a delay of at least 10.24 s which was a standard period to discover the classical Bluetooth devices in range [61]. Improvements to the classical approach [62] and newer Bluetooth Low Power (BLE) technology offer faster discovery phase; however it may still require a relatively large inquiry window to discover all the devices in the vicinity [63]. A computationally faster positioning algorithm will also be more attractive compared to a time-intensive one especially for client-based IPSs with limited resources.

Latency also comprises of another important component for fingerprinting solutions, i.e., how fast the training part of the positioning algorithm can be completed using the collected database. Machine learning techniques, such as neural networks [36,64,65] or support vector machines (SVMs) [30,38] or genetic algorithms (GAs) [49] may take several hours to even days to converge to solution depending on the training database size. This has a significant impact on the performance of the IPS because it has the risk of running the system built upon a stale database for some period.

3.2. Calibration-free performance comparison criteria

3.2.1. Map requirement

A typical fingerprint based localization scheme so far assumed the availability of an indoor map [9,8,10,28]. During site survey, the laboriously captured signal signatures are annotated with their recorded locations inside the map, and then stored inside the database as a <location, signal fingerprint> tuple by the surveyor.

It is a reasonable assumption for the traditional schemes to assume the availability of the map because of the collection procedure being carried out inside a controlled environment. However, this assumption does not hold anymore for the calibration-free schemes where any layman with a wireless device may contribute to the training phase being oblivious of the whole procedure [49,66]. This layman may not even be a regular occupant (may just be a visitor) of this indoor environment. Therefore, those calibration-free solutions that can operate without the map requirement assumption offer more practicality than the others.

3.2.2. Acquiring location fix

Some calibration-free schemes may require the occasional location fix from user devices collected via GPS or other means in order to offer reasonable accuracy [49] while others do not [67]. Initial accurate location fixes are quite important for the overall performance of the system. An IPS that is capable of providing comparable accuracy similar to other approaches without the need of any location fix is certainly more attractive.

3.2.3. Seamless user participation

The key idea behind the calibration-free schemes is to involve users to participate implicitly in order to construct the training database. Any user carrying a wireless device may be expected to contribute to the radio-map construction after agreeing to some initial terms and conditions, or without even being informed about it. This seamless user participation is more attractive compared to the scenario where the user explicitly inputs location fingerprint data as a feedback to the system (e.g., [68–71]). In other words, the lesser the requirement of knowledge on part of the user in building the system, the more desirable the system is.

3.2.4. Usage of indoor landmarks

Many of the previous fingerprinting techniques assumed the knowledge of Wi-Fi APs' locations [31] or even placed sniffers at known positions [72,45]. These locations termed as indoor landmarks are required to be known *a priori* for the positioning system to operate. For example, a model-based localization scheme first estimates the propagation parameters (e.g., path-loss exponent) during the training phase [8,6]. Subsequently, it approximates the distance of the target during localization from at least three known landmarks, and applies trilateration to find its position. One of the motivation of the newer approaches is the ability to seamlessly integrate the system preferably anywhere without any *a priori* knowledge about the layout of the deployment area or its components (e.g., APs' locations).

3.2.5. Need for additional sensors

SurroundSense [59] opened the door for various ambient sensors to be collectively used for localization, and subsequently many works followed suit [73,74,66]. Most of these works assume the availability of these sensors in the mobile phones carried by the crowdsourcing users. Even if the newer smartphones come with most of these sensors (e.g., accelerometer, gyroscope, compass, etc.) built-in, an approach that has a wide range of sensor requirements may be restricted in its applicability, or may result in lower user-base.

3.2.6. Addressing device heterogeneity

Device heterogeneity has been identified as a cause for affecting the localization accuracy in [45,32,43,42,44]. For example, some RF fingerprints tend to vary significantly with the device's hardware under the same wireless conditions. Consequently, fingerprints collected by different devices tend to be quite different from one another. The newer calibration-free techniques are expected to incorporate all the users possibly carrying heterogeneous devices even during the training phase. Therefore, the positioning system should be designed in such a way that it accounts for the fingerprint discrepancy caused by the heterogeneous devices that the user may carry.

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4. Site-survey-free indoor positioning systems

In this article, we provide an insightful summary of the state-of-the-art IPS that does not require any site survey process. We select some interesting research in this section that comes close to achieving this property, and also touch upon their relative advantages and disadvantages. Finally, the performance of each discussed IPS is outlined according to both traditional and calibration-free performance comparison criteria inside Tables 3 and 4, respectively. A list of common notations that are used inside the description appears in Table 2.

4.1. TIX

TIX [75] works only with on-line Wi-Fi RSS measurements, thereby getting rid of the laborious site-survey process. After receiving the location query from a client, TIX's location server sends request to both the client, and all the APs to retrieve the RSSs. For example, if there are m APs, then each AP will report the other $(m-1)$ APs' RSSs, and the client will report m RSS measurements where all APs have coverage over the whole localization area. With the assumption that RSS (log-scale) decays linearly with distance, a linear RSS-to-distance mapping can be obtained at each AP for the other $(m-1)$ APs. Then the client uses the approximated mapping curves of the AP from which it is receiving the strongest signal to obtain its distance to the other $(m-1)$ APs. For its distance approximation to the strongest AP, it uses the mapping curve from the second strongest AP. For the example scenario of Fig. 2, AP_1's constructed mapping curves of AP_2 and AP_3 will be used to approximate the distances between the client and the two APs whereas AP_3's constructed mapping curve of AP_1 will be used for inferring the distance from AP_1. Thereafter, the final location estimate is obtained using the approximated distances between the client and APs, and the APs' location coordinates. For this, TIX utilizes Triangular Interpolation and eXtrapolation (TIX) algorithm [75]; other lateration based algorithms (e.g., triangulation) could also be used.

TIX achieved 5.4 m localization accuracy with zero calibration effort inside an office environment with an area of 1020 m^2. TIX does not require the floor plan information to be operational, but it requires AP's location information. TIX may also warrant modifications of a typical AP's operations in the form of receiving and replying RSS queries from/to the location server.

4.2. SDM

Signal-distance map technique, SDM [76] develops a localization algorithm that only utilizes the on-line RSS measurements to locate the client device. No laborious site survey process to construct the radio map is necessary. Inter-AP RSS measurements are made periodically to automatically calibrate RSSs in the spatio-temporal domain. A truncated singular value decomposition (SVD) technique is then applied to map the relationship of the RSS measurements and the geographical distances to the APs where the APs' locations are assumed to be known. The goal of this on-line mapping is to mitigate the adverse effect of the measurement error, and retain as much recent environmental information as possible by getting rid of the training phase. The least square method is used with the following objective function to minimize:

$$e_i = \sum_{k=1}^{m} (\log(d_{ik}) - b_i s_{ik}),$$

where d_{ik} is the distance between ith AP and each AP k ($d_{ii} = 0$), and $s_{ik} \in \mathcal{S}, k = 1, 2, \ldots, m$, are the perceived RSSs of the ith AP from every other AP. Consequently, the coefficient vector can be solved as, $b_i = \log(d_i^T)\mathcal{S}^T(\mathcal{S}\mathcal{S}^T)^{-1}$. The SDM can then be expressed as, $\mathcal{B} = \log(\mathcal{D})\mathcal{S}^T(\mathcal{S}\mathcal{S}^T)^{-1}$ where $\mathcal{D} = [d_1, d_2, \ldots, d_m]$ and $d_i = [d_{i1}, d_{i2}, \ldots, d_{im}]^T$ are the geographic distance matrix and vector, respectively. Its working principle is almost similar to TIX discussed above which also uses inter-AP measurements to obtain mapping functions. However, its algorithmic operations is quite different compared to TIX. In SDM, the coefficient b_i associated with a particular AP i is computed by taking into account all of ith AP's measurements collected inside the rest $(m-1)$ APs. On the contrary, the ith AP's mapping curve co-efficient will be different at each AP considering only its collected measurements at that particular AP for TIX.

During the location determination phase, a client j first measures the RSSs from its neighboring APs, and retrieves the coefficients b_i's associated with each AP i. It then computes the geographical distances to the neighboring APs as $d_j = \exp(\mathcal{B}s_j)$. Thereafter, lateration technique is used to compute the client's final location estimate using the distance approximations from the APs.

SDM does not require the floor plan map to operate, but it needs to know the locations of the APs. Its localization accuracy is within 3 m inside a small academic departmental building, and performs better than TIX [75]. It may require a little pre-deployment effort though unlike TIX in the form of AP's RSS to distance mapping construction phase. It may also warrant modifications of a typical AP's operations, or additional deployments of monitor/sniffer elements.

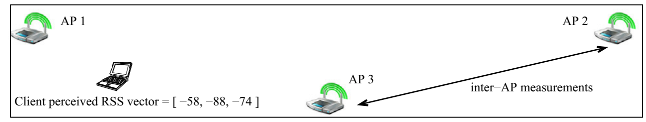

Fig. 2. In TIX and SDM, inter-AP RSS measurements are used in order to infer distances between the target and each AP.

Table 2
A list of the common notations used in the state-of-the-art literature description in Section 4.

Symbol	Meaning
n	Number of training locations
m	Number of APs
d_{ij}	Geographical distance between location i and j
s_{ik}	Observed RSS at location i from AP k
s_i	Observed RSS vector at location i, i.e., $[s_{i1}, s_{i2}, \ldots, s_{im}]$
i, j, k	Used as index variables

4.3. OIL

The organic indoor location (OIL) [77] merges the "training" and "use" phases of a typical fingerprint based localization. In other words, it involves the users of the location system to also contribute to build the radio map simultaneously. Since OIL runs as a daemon process on the client providing localization service, it determines on its own to prompt the user for giving feedback. It may also discard the feedback based on a filtering mechanism. For location determination, it uses the probabilistic maximum likelihood estimator (MLE).

OIL uses voronoi region to map spatial uncertainty of its location estimate, and prompts the user for *explicit* location feedback if the estimation confidence falls below a threshold. The user will only be prompted if his/her feedback is likely to either increase the system's coverage or improves the input location's accuracy. During the prompt, only the voronoi regions which meet a certain similarity metric w.r.t. observed APs (e.g., the number of matched MACs between the candidate and the client that provided fingerprint) are included in the feedback choices. The partial map with those associated voronoi regions only need to be made available to the client, thereby not overwhelming it in terms of computation and storage resources. Additionally, it handles the erroneous user feedback by outlier detection in signal space, i.e., the observed RSSs for each AP. It uses agglomerative hierarchical clustering approach to group the user feedback by similarity. The distance between inter-cluster (C_i and C_j) feedback pairs is represented as:

$$D_S(C_i, C_j) = \frac{1}{|C_i||C_j|} \sum_{(s_i,s_j)\in(C_i,C_j)} d_S(s_i, s_j)$$

where $d_S(s_i, s_j) = [\frac{1}{M}\sum_{k=1}^{m}(s_{ik} - s_{jk})^2]^{\frac{1}{2}}$ is the dissimilarity metric between two feedback RSSs s_i and s_j. $M \leqslant m$ is the subset of total m APs for which its RSS appears in either s_i or s_j. If only one of them appears, the missing value is replaced by -100 dBm. A correct cluster C_l^* given a feedback at location l is identified as:

$$C_l^* = \arg\min_{C\in C_l} \sum_{k\in\mathcal{N}(l)} D_S(C, C_k^*)$$

where $\mathcal{N}(l)$ is the neighboring location set of l, and C_k^* is the correct cluster for location k during the time of computation. The localization algorithm will only incorporate the feedback if the feedback location corresponds to the correct cluster location.

OIL requires the availability of a map, and active participation on the part of the users. In order to build a responsive system for user feedback, the client maintains a local cache of partial fingerprint database which affects OIL's scalability.

4.4. EZ

EZ [49] relaxes the requirement of prior knowledge of indoor RF environment, that would have been laboriously captured during the site survey process of a traditional fingerprinting technique. The received signal strength (RSS) measurements are implicitly reported by EZ clients running inside a user's mobile device without any human intervention. Such automated operation brings forth a number of challenges that have been addressed in [49], e.g., extracting only the *useful* measurements, and efficiently building the indoor RF model based on these measurements.

EZ's built RF model's core lies in the log-distance path loss (LDPL) formula:

$$s_{ik} = s_{i0} - 10\gamma_i \log d_{ik}, \quad (1)$$
$$\text{where } d_{ik} = \sqrt{(x_k - c_i)^T(x_k - c_i)}.$$

Eq. (1) represents the RSS of the kth mobile user's device located at a distance d_{ik} from the ith AP. Suppose x_k and c_i denotes the mobile user and AP's location in 2D, and γ_i is the path loss exponent concerning ith AP's signals. With the RSS measurements collected implicitly from user devices, EZ tries to build the radio-map of the indoor environment. Each RSS measurement from an AP at a particular location is fitted into (1) where the AP's (γ_i, c_i, s_{i0}), and the location, x_k are unknown parameters. If there are m APs and n locations where each AP is seen, then the total number of LDPL equations will be mn, and the total number of unknowns is $4m + 2n$ where the location is represented in 2D. EZ works according to the principle that given enough RSS measurements (i.e., $mn > 4m + 2n$), the system will be uniquely solvable. EZ uses Genetic Algorithm (GA) to come up with the solution, i.e., a vector of all the unknown values to be solved in the LDPL equations. Gradient Descent (GD) is also used inside GA for refinement purpose. As their GA progresses, solutions with higher fitness evolve, and it terminates if there is no improvement for ten consecutive generations.

During the execution of the GA, first the parameters of the APs are determined with as many known locations as possible. Then the unknown locations from which at least three of these *determined* APs can be heard are solved via triangulation. These determined locations in turn result in more APs' parameters to be solved. This process continues until the vector of all the unknowns of APs and locations have been determined. Various techniques are also adopted in order to reduce the search space of the GA in achieving this purpose, i.e., if an AP is heard from five or more *determined* locations, its parameters can be uniquely solved. Again, if it is heard only from four *determined* locations, there are two possible solutions for it, and so on. The indoor RSS model is built offline using the GA that may even take hours to converge depending on the specifics of the indoor space and the amount of measured data. Subsequently, the location queries from the EZ clients are answered by the EZ server in real time using this built model.

EZ also addresses some additional inherent research challenges that come with this automated radio-map building process, e.g., choosing the right set of APs that tries to achieve the maximum entropy of the selected APs' collective information, or the right subset of measurement data that are picked in a similar fashion. EZ also tackles the device heterogeneity issue that might arise because of the involvement of different users (thereby different mobile devices) in building the radio-map. EZ introduces a receiver gain parameter in the LDPL Eq. (1), that varies with mobile devices' hardware. It eliminates the effect of receiver gains by subtracting one mobile device's RSS from another corresponding to an AP. It tries to cluster the *similar* difference readings with the assumption that probably they are taken at the same location or at locations close to each other. Thereafter, the relative receiver gains w.r.t. a random device's gain can be computed using these measurements.

EZ's no pre-deployment site survey effort comes at the cost of some accuracy loss compared to traditional fingerprinting techniques such as RADAR [8] or Horus [10]. EZ does not demand the knowledge of physical layout (i.e., map) of the indoor environment or even the location and transmit power information of the APs to be known. This particular feature together with no pre-deployment effort make it a feasible localization solution inside indoor settings such as malls, and multi-tenant commercial buildings where different APs might be deployed/managed by different entities. However, EZ works upon the assumption that the users carry Wi-Fi equipped gadgets over the indoor environment that has excellent Wi-Fi coverage throughout, and also the availability of occasional location fix, e.g., GPS lock at the edges of the indoor setting.

4.5. WiGEM

WiGEM [78], a wireless localization algorithm using Gaussian mixture model (GMM) with expectation maximization utilizes model based parameter estimation, thereby relieving the site survey process. It then applies maximum *a posteriori* estimation algorithm on the created model in order to locate the client.

This infrastructure-based learning oriented approach requires sniffers at *known* positions in order to collect Wi-Fi RSS measurements from the client. The RSSs at the sniffers are then represented by GMM:

$$p(s) = \sum_{j=1}^{J}\sum_{k=1}^{K} \upsilon_j \tau_k N(s|\mu_{(j,k)}, \sigma^2_{(j,k)}),$$

where υ_j is the probability of the client being at location j, and τ_k is the probability of transmit power level being k, and s is the RSS vector measured at the deployed sniffers. $\mu_{(j,k)}$ and $\sigma_{(j,k)}$ are the mean and standard deviation of the measured RSSs given the client is stationed at location j with transmit power level k. The parameters of the GMM are $\theta = (\upsilon, \tau, \mu, \sigma)$.

The area of interest is first divided into J grid locations, and υ and τ are assumed to be uniformly distributed over all possible locations, and power levels, respectively. Initial μ is computed using Eq. (1) for each $j \in J$. This is possible since the sniffers' locations are known. σ's value is fixed at 5 for all sniffers. Given one RSS vector, s, the GMM model parameters are then updated using expectation maximization technique which will eventually converge by associating the RSS vector with a particular location of the client, j.

Real-time localization is then performed by first finding the probability for each (location, power-level) pair given an observation RSS s^{obs}, and then marginalizing it over the power levels. The location with the highest probability will then be returned as the client's final location estimate:

$$j^* = \arg\max_j \sum_k p(x_j = 1, z_k = 1 | s^{\text{obs}})$$

WiGEM follows traditional model-based fingerprinting techniques in its working, but takes into account the client device heterogeneity and their different transmit power level issues. It is an important aspect for WiGEM to consider because of its infrastructure based approach. Furthermore, WiGEM assumes the RSS to follow Gaussian distribution which is received with mixed reactions in the literature. It also requires the availability of a map, and the sniffers' locations to be known.

4.6. WILL

WILL [67], a wireless indoor logical localization approach relieves the site survey process in constructing the training database while providing comparable accuracy and precision. WILL utilizes the commonly seen property that the RSS goes through significant change through a wall, and an accelerometer's reading can be used to detect whether a user is moving or stationary.

WILL captures the user traces as a series of $\langle F, A \rangle$ values, where F and A indicate the Wi-Fi signal fingerprint and accelerometer values, respectively. Depending on the similarity of the fingerprints, they are grouped inside the same *virtual* room or a different one. Subsequently, a logical floor plan is conceived which is a diagram depicting the reachability among virtual rooms utilizing the user traces. Some filtering techniques are also adopted where traces with few steps or APs are discarded. The actual physical floor plan is also converted to a graph where an edge between two nodes (i.e., rooms) indicates the reachability between them. The logical floor plan is then mapped onto the physical one utilizing some vertex matching techniques between two graphs, e.g., skeleton mapping, and branch-knot mapping [67,79]. Redundant information like neighboring information of the mapped vertices are also utilized to correct the mapping errors of the mapping process. Once completed, the location queries can then be answered by the localization engine which uses the fingerprint database to first localize the virtual room, and then obtains the corresponding physical room from the mapping.

WILL provides 86% room-level accuracy without the requirement of measurement feedback from known locations, or the knowledge of APs' locations. However, it requires the map of the space of interest for the virtual to physical room mapping process.

4.7. UnLoc

UnLoc [66], an unsupervised indoor localization scheme, utilizes urban dead-reckoning [80] to track a user while recalibrating its estimate whenever it encounters a *landmark* (e.g., an entity with known location). The landmarks are categorized into two: (i) seed landmarks (SLMs) are the elevators, escalators, stairs, entrances etc., that may exhibit distinct signatures in the inertial sensory dimension, and (ii) organic landmarks (OLM) are small confined geographical areas that exhibit distinct patterns from many sensed signals (Wi-Fi, inertial sensors, etc.). UnLoc identifies both types of landmarks in an automated manner during the crowdsourcing process. For example, a Finite State Machine (FSM) is used on the accelerometer readings to separate the various SLMs, while an OLM is identified based on two different locations' similarity metric, $\lambda \in \{0, 1\}$:

$$\lambda = \frac{1}{|m|} \sum_{\forall k \in m} \frac{\min(s_{1k}, s_{2k})}{\max(s_{1k}, s_{2k})}, \tag{2}$$

where s_{1k} and s_{2k} denote the RSSs of AP $k \in m$ at location l_1 and l_2 respectively. The rationale behind (2) is to add proportionally larger weights to λ when an AP's signal is strong at both l_1 and l_2, and vice versa. (2) helps to identify Wi-Fi based OLMs in a way that all locations within the Wi-Fi landmark exhibit lower similarity (e.g., $\lambda < 0.4$) with the rest. Moreover, all estimated locations within the Wi-Fi based OLM must be confined inside a small region ($4\ \text{m}^2$) to be considered as a *single* landmark. Similar technique has been adopted for identifying other inertial sensor based OLMs.

UnLoc works in the following manner – the mobile user starts the itinerary whenever he/she encounters the first landmark (e.g., entrance), and subsequently *resets* the position whenever other landmarks are sensed. The dead-reckoning approach is used to track him/her between landmarks. The locations of the landmarks are made more accurate as more user traces become available which in turn improve dead-reckoning tracking of subsequent handhelds. This recursive process continues to improve UnLoc's offered accuracy over time, while the first few crowdsourcing users might suffer from inferior accuracy.

UnLoc does not require the floorplan to operate, but it needs only one seed landmark's location during bootstrapping phase (e.g., the entrance) to be treated as origin for the space of interest. UnLoc demonstrates a median error of 1.69 m across three different indoor settings including a shopping mall; however they conducted all the experiments with a single mobile device.

4.8. Zee

Zee [73] utilizes inertial sensor measurements of a user's smartphone (e.g., gyroscope, compass, accelerometer, etc.) to track his/her movement/direction, and subsequently annotates the locations traversed with the Wi-Fi RSS measurements. In other words, Zee uses Wi-Fi and inertial sensor readings crowdsourced from the users' handhelds to construct the Wi-Fi training set which was otherwise being laboriously constructed by a site survey process.

Zee works according to the following principle – a user's traveled distance and direction might be obtained from accelerometer and compass/gyroscope data. Now, with the help of a map, certain constraints can be applied to the user's traversed path which may ultimately result in revealing the user's final location. For example, according to the map, only one pathway inside the area may accommodate the user's traveled path at a certain time. Consequently, we can also infer the user's starting location, and thereby can annotate the whole pathway locations with measured Wi-Fi data. Zee has two main components:

- Placement Independent Motion Estimator (PIME) identifies whether the user is walking or not; irrespective of where the handheld might be placed (e.g., front/back pockets, bags, etc.), and also estimates the step count and heading offset (HO).

- Augmented Particle Filter (APF) maintains a four dimensional joint probability distribution of the user's location (x, y), stride length, and HO along his/her traversed path.

The APF then runs belief back-propagation (with map constraints) to correct the user's path history as described before. This yields a time-indexed sequence of the user's estimated locations that can be annotated with the measured Wi-Fi RSSs. As the training database gets filled with more Wi-Fi measurements, the APF may obtain a more confined belief of the user's initial location distribution (for the first user, it would be uniformly distributed over the whole space of interest) by comparing the Wi-Fi scans with the existing database. The Wi-Fi measurements obtained from subsequent walk are in turn used to refine the existing database.

Zee is not a localization algorithm, rather an innovative means of constructing the training radio-map from crowdsourcing which could be used by any location fingerprinting techniques. With Zee's crowdsourced data, Horus [10] and EZ [49] were seen to achieve a median localization error of 3 m, comparable to the performance achieved by using the typical site surveyed training data. Zee does not require any location fix (e.g., GPS lock), and is also free from requirement of knowledge of the APs' locations. However, it requires the availability of a map of the space of interest during the crowdsourcing process.

4.9. LiFS

Locating in fingerprint space (LiFS) [74] is an indoor localization system from the same group who invented WILL discussed in Section 4.6. LiFS follows similar principle as WILL [67], and also uses off-the-shelf Wi-Fi infrastructure, and inertial sensors (accelerometer) of mobile devices in order to locate a target. LiFS training phase is divided into three main tasks: (i) transforming the map into a stress free floor plan, (ii) creating fingerprint space, and (iii) mapping between fingerprint and real location. The client's location queries are then answered with the *closest* location corresponding to the observed fingerprint (nearest neighbor); even though other searching algorithms can easily be adopted.

The stress free floor plan is created by first sampling the real floor plan into grids, where two consecutive grids' separation is set at 2 m. By calculating walking distances between all sampled locations (via accelerometer readings of user traces), a distance matrix $D = [d_{ij}]$ can be obtained between every two locations i and j. In a stress free floor plan, the Euclidean distance between a pair of points reflects the walking distance of their corresponding locations in a real floor plan. Fingerprints are recorded during a normal user's itinerary together with the walking distances (via computing steps multiplied by stride length) between two consecutive recorded fingerprints. These fingerprints are pre-processed to filter out the multiple similar fingerprints taken *possibly* at the same positions. The fingerprint space is then constructed by connecting the fingerprints collected with the distance information using Floyd–Warshall shortest path algorithm [81]. Subsequently, the mapping between each fingerprint with a real location can be performed utilizing the spatial similarity between the constructed stress-free floor plan and the fingerprint space. Similar to WILL [67], betweenness centrality and k-Means algorithm are used to identify the fingerprints along the corridors and rooms, respectively. Thereafter, fingerprints observed at doors (named *reference points*) are utilized to match the different clusters (i.e., corridors and rooms), thereby establishing the correspondence between the stress free floor plan and the fingerprint space. Subsequently, the points in each cluster are mapped to sample locations in its corresponding rooms by choosing the nearest neighbor for each point.

LiFS offers 89% room-level accuracy (average localization error 5.8 m) inside a medium sized academic building. It does not need to know the APs' locations, but requires map to transform it into a stress free floor plan with associated fingerprints.

4.10. Walkie-Markie

Walkie-Markie [82] generates indoor pathway maps from crowdsourcing user traces without any *a priori* knowledge about the space of interest (e.g., map, propagation characteristics, etc.). They utilize RSS trend (increasing or decreasing) rather than its absolute values by identifying *Wi-Fi marks* inside the building where RSS trend tripping point (RTTP) (i.e., maximum) occur for an AP. They argue that using RTTP's location as Wi-Fi marks is free from mobile device heterogeneity, and other environment factors affecting absolute RSS. These Wi-Fi marks are then placed inside the 2D plane by their graph embedding algorithm utilizing user trajectories. On one hand, the created pathway maps leverages the localization of users when they pass a Wi-Fi mark, and utilizes dead-reckoning to localize him/her in between two Wi-Fi marks. On the other hand, the pathway maps can also be utilized to create the complete radio map of the space of interest, thereby opening the door for traditional fingerprinting techniques to be used on top of it.

Wi-Fi mark is identified by $\{\mathrm{BSSID}, (\mathcal{D}_1, \mathcal{D}_2), \mathcal{N}\}$ where BSSID is the AP's MAC, $\mathcal{D}_1$ and $\mathcal{D}_2$ are the steady walking directions approaching and leaving the RTTP, respectively. Furthermore, the neighbor information $\mathcal{N}$ of the AP is used to resolve ambiguity that might occur in case of parallel corridors or similar turning styles. Walkie-Markie then uses the direction information together with distance information retrieved from user trajectories in order to place the Wi-Fi marks at real locations using their novel "Arturia" positioning algorithm. Due to the possibility of Wi-Fi marks being reported differently (i.e., at different locations) by multiple crowdsourced trajectories, a clustering algorithm is used in order to cluster the Wi-Fi marks with slight deviations into a single one. Utilizing the placed Wi-Fi marks' locations together with user trajectories, an expansion and shrinking process is then applied to conceptualize the whole pathway map.

Walkie-Markie's average localization error is 1.65 m outperforming RADAR (2.3 m) in the same office floor testbed of area 3600 m^2. It neither requires the knowledge of the floor plan nor needs to know the locations of the APs.

5. Discussion

Some of the recent calibration-free fingerprinting IPSs discussed in the previous section are evaluated w.r.t. performance comparison criteria discussed in Section 3 in Tables 3 and 4. From the tabulated evaluation results, one can select the IPS that may best suit his/her location-based application's requirements. In the following, we provide an overall discussion based on the findings.

None of the work seems to report accuracy and precision in terms of both localization performance numbers (e.g., median or average error) and room-level correctness with the exception of LiFS which reports average localization error and room-level error to be 5.8 m and 11%, respectively. The rest either provide numbers (e.g., SDM, EZ, etc.) or the room-level accuracy (e.g., WILL). As discussed in Section 2, both types of performance evaluation results are important for indoor environment. The performance results also vary according to the testbed size as reported in EZ [49]. Both scalability and robustness issues are addressed in newer approaches (e.g., WILL, UnLoc, Zee, LiFS, Walkie-Markie, etc.) rather than the earlier ones (e.g., TIX, SDM, OIL, etc.). The newer systems are also quite cost-effective in terms of its deployment parameters,

Table 3
Performance of state-of-the-art site survey free research w.r.t. traditional performance comparison properties.

	Accuracy and precision	Scalability	Robustness	Security and privacy	Cost and complexity	Wireless technology	Latency
TIX [75]	Average error ~5.4 m inside an office building (1020 m^2)	Partially because of AP dependence	Partially; linear mapping of RSS and log(distance)	Yes; client computes its own location	Requires modified APs' operations; simple computationally light algorithm	Wi-Fi	No database creation; slow responsiveness to client queries that involves first retrieving the RSSs from APs (inter-AP measurements) and client, followed by mapping function, and then location estimation
SDM [76]	Average error ~3 m inside small building (598 m^2)	Partially because of AP dependence	Partially; linear mapping of RSS and log(distance)	Yes; client computes its own location	Requires modified APs' operations or additional sniffer elements; simple algorithm	Wi-Fi	No database creation, only linear coefficients estimations by the APs; client computes its location quickly using lateration technique
OIL [77]	Accuracy and precision numbers are not reported	No; client has to maintain local cache of fingerprints	Partially	Yes; client computes its own location	Uses off-the-shelf h/w; simple MLE algorithm	Wi-Fi	Server updates client's local cache, and also filters out erroneous feedback; fast response time using simple MLE by the client itself
EZ [49]	Median error ~2 m inside small building (486 m^2) and 7 m inside big building (12,600 m^2)	Yes	Partially; model based	No	Uses off the shelf h/w; complex algorithm	Wi-Fi	Because of GA, construction of EZ database is time intensive; answer to location queries of EZ clients in real time though
WiGEM [78]	Better than other model based techniques but poorer than RADAR [8] and probabilistic [10] approaches with finer granularity inside two testbeds – one small (600 m^2) and another medium sized (3250 m^2) academic buildings	No; finer granularity RSS reading is required	Partially; model based	No	Infrastructure-based; Requires sniffers or modified APs' operations; complex GMM creation and EM algorithm	Wi-Fi	WiGEM model creation can be offloaded to cloud server machines since infrastructure-based approach; increases monotonically with learning samples. Response to location queries in real-time, but responsiveness depends on the granularity of the location area used
WILL [67]	86% room level accuracy inside medium sized academic building (1600 m^2)	Yes	Yes; Performs major (occasionally) and minor (frequently) updates that keeps the training database up to date	No	Uses off the shelf h/w; Complex mapping of virtual floor into physical layout with associated fingerprint	Wi-Fi	Construction of training database is incremental; response to client location queries is fast using simple pattern matching technique
UnLoc [66]	Median error ~1.69 m across three different indoor setups (largest being 4000 m^2)	Yes	Yes	No	Uses off the shelf h/w; Simple techniques to identify SLM and OLM together with dead-reckoning scheme	Wi-Fi (also reliant on inertial sensors for localizing)	Convergence to training database is fast; so also the answer to location queries using simple matching and dead-reckoning
Zee [73]	Median error ~3 m inside medium sized building (2275 m^2) when used together with EZ or Horus	Yes	Yes	No	Uses off the shelf h/w; Constrained based simple filtering techniques	Wi-Fi	Construction of training database is fast; training database is used with other algorithms to answer location queries (e.g., EZ, RADAR, etc.)
LiFS [74]	89% room level accuracy inside medium sized academic building (1600 m^2)	Yes; Even though their fingerprints are collected at finer granularity	Yes	No	Uses off the shelf h/w; Complex training phase and also requires little calibration effort to construct the stress free floor plan	Wi-Fi	Construction of training database is incremental; response to client location queries is fast using simple pattern matching technique
Walkie-Markie [82]	Average error ~1.65 m inside a medium sized office floor (3600 m^2); also conducted some experiments inside a shopping mall	Yes	Yes	No	Uses off the shelf h/w; novel algorithm to identify Wi-Fi marks, their real locations and the overall conceptualization of the whole pathway map	Wi-Fi (also reliant on inertial sensors for localizing)	Convergence to training database is fast; so also the answer to location queries using simple matching and dead-reckoning

Table 4
Performance of state-of-the-art site survey free research w.r.t. calibration-free performance comparison properties.

	Map requirement	Acquiring location fix	Seamless user participation	Usage of landmarks	Need additional sensors	Address device heterogeneity
TIX [75]	No	Yes; from APs with known locations	N/A	Yes; APs treated as landmarks	No	No
SDM [76]	No	Yes; from APs with known locations	N/A	Yes; APs treated as landmarks	No	No; presented results do not verify its claim of addressing device heterogeneity
OIL [77]	Yes	Yes, from users	Explicit	No	No	No
EZ [49]	No	Yes; needs occasional fix from known locations (e.g., GPS lock)	Implicit	No	No	Yes
WiGEM [78]	Yes	No	Implicit	No	No	Yes; supported with experimental results, however explanation is missing as to why their approach can handle device heterogeneity
WILL [67]	Yes	No	Implicit	No	Yes; accelerometer	Yes; using RSS stacking difference similar to [42,44]
UnLoc [66]	No	No; only one SLM's location needed during bootstrapping	Implicit	Yes; both SLM and OLM retrieved from user traces	Yes; accelerometer, gyroscope & compass	No; all experiments are performed with one type of device
Zee [73]	Yes	No	Implicit	No	Yes; accelerometer, gyroscope & compass	N/A; produces training radio-map via crowdsourcing to be used with other fingerprinting techniques
LiFS [74]	Yes	No	Mostly implicit; only stress free floor plan construction requires explicit participation	No	Yes; accelerometer	No; Same device used for the experiments
Walkie-Markie [82]	No	No; only one landmark's location with absolute location during bootstrapping	Implicit	Yes; Wi-Fi marks retrieved from user traces	Yes; accelerometer, gyroscope & compass	Yes; usage of RTTP to identify Wi-Fi marks, and also RSS differences during clustering of Wi-Fi marks

and operational characteristics except for LiFS [74]. However, handling security and privacy gives a different picture, i.e., most of the newer approaches like WILL, UnLoc, Zee, LiFS, Walkie-Markie do not address it. Most of the approaches' responsiveness to location queries are fast with the exception of TIX. All of them utilize existing Wi-Fi infrastructure as the wireless technology in their localization algorithm while a few also use inertial sensors on top of it (e.g., UnLoc, Walkie Markie, etc.).

The map requirement parameter produced mixed observations for the calibration-free systems as seen in Table 4. The ones that required map knowledge argue that a user needs to be shown inside a map to consume location-based services [73]; so it does not make sense assuming the unavailability of the map. Furthermore, various map construction tools are already available in the literature [83]; so the map availability assumption can be safely made. Most of the earlier works (TIX, SDM, OIL, or even EZ) require location fix from known locations while the more recent ones do not. User participation is implicit inside the most recent ones' workings. On the contrary, either explicit user participation was generally required for earlier research (e.g., OIL) or the user participation was ignored altogether (e.g., TIX or SDM). TIX and SDM use APs with known locations as landmarks whereas *organic* landmark is conceptualized without any *a priori* knowledge in the newer systems like UnLoc and Walkie-Markie. The recent systems (WILL, UnLoc, Zee, LiFS, Walkie-Markie) also require additional sensors on the client devices besides Wi-Fi to be operational which is argued to be quite commonplace for today's handhelds. Very few systems like EZ, WILL, Walkie-Markie address the client device heterogeneity issue which may have biased other systems' accuracy or precision reporting (e.g., UnLoc and LiFS).

In this survey, we have only selected the class of calibration-free techniques that utilizes the ubiquitous Wi-Fi infrastructure as the main means for localization. Moreover, it incorporates the off-the-shelf hardware integrated with various handhelds making the system to be an easily deployable low-cost solution. We feel this class of systems has huge potential since it follows the traditional fingerprinting approach's principle that already showed promise for indoor localization.

Tables 3 and 4 can help the reader to quickly identify the appropriate calibration-free solutions that can satisfy a application's need. If an application's requirement is specified in terms of the various performance properties, e.g., accuracy/precision, cost/complexity, addressing device heterogeneity, map requirement, usage of inertial sensors, etc., the corresponding solutions that satisfy these requirements fully or partially can easily be identified by going through the summarized results/findings presented inside the tables. For example, if one is interested in the class of calibration-free positioning systems that do not require any inertial sensors but addresses the device heterogeneity, one quick look at the last two columns of Table 4 will reveal that EZ and WiGEM will fall into that class of positioning systems.

Another class of calibration-free techniques, namely Simultaneous Localization and Mapping (SLAM) [84] utilizes *only* the inertial sensors to iteratively construct the indoor environment map, and localizes the user within this map. SLAM was initially targeted at robotics and autonomous vehicles field in order to construct a map within an unknown environment, while at the same time keeping track of their locations. However, it is slowly finding its way in the calibration-free indoor localization as well where a user can be located inside a map that has been created by someone else. It mainly uses various filtering (e.g., Kalman filter, Particle filter, etc. [85,86]) and dead-reckoning [80] techniques utilizing the inertial sensor measurements to build the map without any *a priori* knowledge, and pinpoint the location inside it. A lot of variants of SLAM exist in literature. FootSLAM [87] and ActionSLAM [88] use foot-mounted and body-mounted inertial measurement units

(IMUs) respectively to track a user's motion; PlaceSLAM [89] is an improvement over FootSLAM by explicitly involving users to input feedback about his/her known physical world. WiFi-SLAM [90] uses Gaussian Process Latent Variable Model (GPLVM) together with motion dynamics model to label the unlabeled signal strength data in order to perform efficient localization. GraphSLAM [91] is an improvement over it. Unlike other SLAMs, SmartSLAM [83] uses smartphone's accelerometer, compass, and Wi-Fi modules to observe the device's movement and environment, and thereby construct the indoor map. Although this family of SLAM techniques is quite promising to relieve the exhaustive calibration of a typical fingerprinting technique; their working principle is quite different from the ones discussed in Section 4. Therefore, none of them has been included for thorough evaluation purpose in this article. Moreover, they may require customized inertial sensors that need to be integrated inside a moving object specially (e.g., foot-mounted, body-mounted or having a specific orientation, etc.) to ensure accurate measurements. This may not be in accordance with the property that the low-cost easily deployable IPS must adhere to.

In terms of commercial prospect, the calibration-free indoor positioning start-ups are recently making its presence felt. Most of these commercial products seem to follow the same principles adopted by the calibration-free research that we have discussed in this article, i.e., they use and process the off-the-shelf inertial sensor measurements that are readily available within a modern smartphone. Navigine [92] uses Wi-Fi signals and the inertial sensors found in the smartphones for navigation with claimed accuracy of 1–2 m. On the contrary, Navisens [93] only uses the inertial sensor measurements. Both of these products use filtering algorithm to pinpoint the final location estimate. indoo.rs [94] relies on a combination of dead-reckoning, sensor fusion and partial WiFi fingerprinting for indoor navigation. All of them try to provide SaaS (software as a service) by giving out an SDK for the developers to program various applications on top of their location service to run in their smartphones.

6. Conclusion and future work

In this article, we reviewed the calibration-free fingerprinting techniques w.r.t. both traditional and some newer performance comparison criteria that we identify based on the systems' operating principles and characteristics. This newer breed of fingerprinting solutions try to get rid of the training phase of a typical fingerprinting system that generally hinders its widespread deployment in an indoor environment. We selected 10 such calibration-free schemes to discuss in detail, and point out their advantages and disadvantages w.r.t. our identified performance comparison properties. From this survey, the readers will have a comprehensive understanding of the existing calibration-free techniques in the literature, especially of the 10 IPSs discussed elaborately. As can be seen from the discussion, each IPS has its own design characteristics, e.g., it uses a certain kind of technology like Wi-Fi or may include the inertial sensor measurements as well. Moreover, one may work well compared to the other under certain constraints (e.g., with the availability of map or the lack of it). Section 5 provides a discussion on the suitability of a particular calibration-free IPS under certain scenarios or requirements.

We foresee a few future research work directions in order to enhance the prospects of widespread deployability of such techniques. For example, none of the calibration-free research touches upon the important security and privacy issue explicitly; although the prior research of this family (e.g., TIX, SDM and OIL) incorporates it implicitly because of its client-based location computation nature. Starting from EZ [49], the crowdsensing way of eliminating the calibration phase warrants the tackling of security and privacy issue even more which has not been addressed. Even though the user participation is implicit, a malicious user can easily tamper with the system by providing incorrect measurements, thereby delaying the convergence of the system, and also degrading its offered accuracy. Energy efficiency is another aspect for consideration for these crowdsensing approaches. Most of them assume the client devices to turn on the Wi-Fi, and other inertial sensors for obtaining the measurements, which may drain their batteries quickly. In practical scenarios, this might be a road block for deploying such systems. Even though one of the motivation of such calibration-free techniques was its fast and easily deployable quality; in practical sense, it may still require a bit more investigation. For example, in order to offer reasonable accuracy and precision, the participating users may need to be uniformly distributed over the whole space of interest which might be difficult to ensure in practice.

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