Highly-Available Localization Techniques in Indoor Wi-Fi Environment: A Comprehensive Survey

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Abstract. With the increasing interests on received signal strength (RSS) fingerprint-based Wi-Fi localization, the requirement of recording reliable and accurate RSS fingerprints for radio map construction becomes a significant concern. The neighbor matching and Bayesian estimation is recognized as the two most representative algorithms for RSS fingerprint-based indoor Wi-Fi localization. To guarantee the accuracy performance of neighbor matching and Bayesian estimation algorithms, we introduce several method to eliminate RSS sample noise for the sake of improving the distance dependency of Wi-Fi RSS fingerprints.

Keywords: Wi-Fi localization · RSS correlation · Smooth filtering
Neighbor matching · Bayesian estimation

1 Introduction

A large amount of attention has been paid to the design of indoor highly-accurate and reliable localization systems in recent ten years with the significant growth of interests on the ubiquitous context-awareness and mobile computing [1–3]. Due to the requirements of special infrastructures and devices by ultrasonic wave (UW) [4], ultra-wideband (UWB) [5], infrared ray (IR) [6], radio frequency identification (RFID) [7], Bluetooth [8], and inertial navigation system (INS) [9] based localization systems, the received signal strength (RSS) fingerprint-based Wi-Fi localization system is more preferable owing to the advantages of sufficient accuracy in indoor localization, widely-deployed Wi-Fi infrastructures, and free 2.4 GHz Industrial, Scientific and Medical (ISM) band [10–12]. Another good reason to the popularization of indoor Wi-Fi localization is that the Global Navigation Satellite System (GNSS) (e.g., GPS in USA [13], Global Navigation Satellite System (GLONASS) in Russia [14], BD in China [15], and Galileo Positioning System in Europe [16]) cannot work well in urban and indoor environments due to the poor quality of RSS received from satellites. On this basis, we compare several typical indoor location systems in Table 1.

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Table 1. Comparison of several indoor location systems

Systems	Accuracy	Cost	Infrastructures and devices
UW [4]	Cm-level accuracy but limited within a room and easily interfered by sound sources	Extra infrastructures and devices	Multiple UW emitters and receivers
UWB [5]	Cm-level accuracy but strict time synchronization required	Extra infrastructures and devices	Multiple UWB emitters and receivers
IR [6]	Cm-level accuracy but limited within a room and easily interfered by light sources	Extra infrastructures and devices	Multiple IR emitters and receivers
RFID [7]	With errors less than 1 m in passive mode and with errors between 3 m and 5 m in active mode	Extra infrastructures and devices but easily built in	Single RFID tag without battery power in passive mode and multiple RFID tag with battery power lasting for several years in active mode
Bluetooth [8]	With errors between 1 m and 5 m	Extra infrastructures and devices but easily built in	Single Bluetooth beacon for 2D localization and multiple Bluetooth beacons for 3D localization with battery power lasting for several years
INS [9]	With errors less than 1 m but easily interfered by drift	Existing function and easily accessed	Micro-Electro-Mechanical Systems with wide operating temperature range
Wi-Fi [10]	M-level accuracy but easily interfered by environmental factors	Existing infrastructures and devices	Single access point for proximity localization and multiple access points for fingerprintbased and propagation model-based localization

Up to now, there are three typical categories of Wi-Fi localization algorithms: RSS fingerprint-based, time of arrival (TOA) and angle of arrival (AOA)-based, and propagation model-based localization. Based on the consideration of localization accuracy and computation and maintenance cost, RSS fingerprint-based localization algorithm is preferred [17–19]. However, the existence of burst noise, e.g., the adjacent-channel interference from cordless phones, Bluetooth devices, and near field communication devices and the human body and indoor infrastructure shadowing, is recognized as one of the most significant drawbacks of Wi-Fi RSS fingerprint-based localization [20, 21]. In response to this compelling drawback, we propose as a new approach to eliminate the RSS samples which are interfered by burst noise for the sake of improving the accuracy of neighbor matching and Bayesian estimation algorithms in Wi-Fi localization. Much different from many of the existing fingerprint filtering approaches, there is no need to record RSS statistics (e.g., RSS mean, median, maximum, and minimum) and RSS distributions (e.g., Gaussian fitting curves) at each reference point (RP). The localization accuracy is examined in a typical indoor scenario, a straight corridor, which is also used in [17,35,37,38]. The location target is moving in a normal course and only two RSS samples are recorded at each location for the testing. The rest of this paper is organized as follows. Section 2 shows using Wi-Fi technique on Wi-Fi localization. Section 3 shows that Network Deployment and Fingerprint-based Wi-Fi localization system, TOA and AOA-based Localization, Propagation Model-based Localization respectively. Experimental result is discussed In Sect. 3. Finally, we conclude this paper in Sect. 4.

2 Using Wi-Fi Technique

With the remarkable growth of location-based services (LBSs), the work on indoor localization has attracted significant attention in recent decade. The LBSs have ranged from the military to public uses, like the emergency rescue, guidance in airports and unfamiliar buildings, and entity management inside modern buildings, libraries, and warehouses [22,23]. To achieve these goals, the Wi-Fi technique is suggested as a reliable and cost-efficient way to provide the highly-accurate, cost-efficient, and real-time indoor LBSs due to the two main reasons below.

The first main reason is that in many indoor and underground environments, GPS signals cannot be received due to the serious shadowing effect by the buildings and ground. Although the cellular network (e.g., WCDMA) can help to improve accuracy and reduce acquisition time of GPS receiver, the requirement of the additional radio frequency (RF) transceiver modules designed for cellular network significantly increases the device cost and power consumption of GPS receiver. As an alternative to indoor localization, the INS relies on accelerometer, gravimeter, compass, and many other sensors to infer the targets speed, height, orientation, and other actions [9]. The accuracy and scalability of INS are suffered from the error accumulation which is caused by sensor noise and the limited availability of motion sensors. Since the Wi-Fi networks are widely deployed in public hotspots and enterprise locations, the Wi-Fi fingerprint-based localization and tracking become more popular. The average errors by Wi-Fi fingerprint-based localization generally fall into the range between 2 m and 10 m with the response time in a few seconds.

The second main reason of using Wi-Fi technique to conduct indoor localization is that the target can calculate its own locations by itself, namely the mobile-based localization mode, or rely on the network to obtain its locations, namely the network-based localization mode. In network-based localization mode, the access points (APs) relay the received signals to a central location server to do location calculation and then send the localization results back to the target. Since the target is not involved in signal processing and location calculation process, there is no need to modify the conventional Wi-Fi network interface card (NIC) which can be easily designed and embedded into the existing mobile devices.

3 Network Deployment

Since the indoor Wi-Fi localization is normally based on the 802.11a/b/g infrastructures and devices, the deployment and maintenance are cost-efficient for the widespread use [24,25]. Although the targets location can be well-estimated based on three APs in the open environment by using triangulation algorithm, there are always more than three APs required for indoor localization due to the RSS refraction, reflection, scattering, and adjacent-channel and multi-path interference [26]. The network deployment including the deployment of APs and calibration of RPs should also be seriously considered for indoor Wi-Fi localization.

Up to now, there are mainly three representative methods for network deployment: (1) uniform deployment by which the RPs are uniformly calibrated in target environment [27]; (2) non-uniform deployment by which the locations of RPs and APs are optimized based on the criterion of coverage requirement [28]. For instance, the area with high priority of coverage requirement is more likely to be calibrated with more RPs; and (3) Zigzag deployment by which the average RSS difference between different RPs are maximized to improve the location resolution of RSS [29]. The detailed discussion on indoor Wi-Fi network deployment is beyond the scope of this paper. In our experiments, the RPs are uniformly calibrated and the three APs are fixed at the left and right ends of a straight corridor.

3.1 Fingerprint-Based Wi-Fi Localization System

Fingerprint-based localization is based on the calculation of the similarity between the off-line pre-stored fingerprints and the on-line newly recorded samples [17,18]. As the first fingerprint-based Wi-Fi localization system, RADAR defines the Euclidean distances between the fingerprints and the new samples as the similarities and selects the RP with the smallest distance, namely the nearest neighbor (NN), as the estimated position [17]. This process is named as the neighbor matching. If there are RPs to be selected as the NNs, namely the K nearest neighbors (KNN), the targets position can be estimated at the geometrical center of the KNN [17,30], [47]. The accuracy of the original RADAR system is about 4 m with probability [17], while the enhanced RADAR system by using the Viterbi-like algorithm [31] achieves the accuracy around 2.37 m to 2.65 m over 50 percentile and 5.93 m to 5.97 m over 90 percentile. In RADAR system, the response time is mainly determined by the time cost for the traversal of radio map to search for the NN(s). This cost increases dramatically with the dimensions of radio map. For instance, if there are RPs calibrated in target area and sample (of dimensions) recorded at each RP, the number of sample values stored in radio map equals to (Ns * M) * Nr.

Another representative fingerprint-based Wi-Fi localization algorithm to be discussed in this paper is the Bayesian estimation. Marylands Horus [18] is recognized as the most prominent Bayesian estimation based localization system which is featured with high accuracy and low computation cost. Horus mainly focuses on the issues including the relationship between the mean of RSS and the sample number, compensation for small-scale RSS fading, and RSS variations with respect to spatial characteristics. In Horus system, the target is estimated at the RP with the highest likelihood by Bayesian estimation. The experimental results in [32] show that the Horus system can achieve the accuracy of more than 90 percentile within 2.1 m. The increase of the number of samples at each RP improves localization accuracy due to the better estimation of the mean and standard deviation of the Gaussian RSS distribution at each RP. The drawback of Horus system is that a large amount of computation cost is required to calculate the small-scale compensation. For instance, to achieve small-scale compensation, we need to try combinations to perturb samples in our experimental environment which is covered by 9 APs.

Similarly, Castro in [33] developed another Bayesian estimation based localization system, Nibble, to infer the targets locations by using signal quality measurements. Nibble uses a different concept of localization accuracy which is defined as the proportion of correct readings in reading set. A correct reading is counted when the targets actual location is located in its most likely referred area. In [33], by consulting all the APs for each location request, the Nibble system can achieve 97% accuracy. To save computation cost, the Nibble system only consults three most neighboring APs to achieve 96% accuracy. Compared to RADAR and Horus, although the computation cost for coordinate calculation is not considered by Nibble, the recording of location frequency and frequency updating are required. The accuracy of Nibble heavily relies on the deployment of RPs. For instance, if the target is far away from its nearest RP, the localization accuracy cannot be guaranteed. The major difference between Horus and Nibble is the approach to record RSS distributions. The former one fits each RSS distribution as a Gaussian curve and stores the parameters of the fitted Gaussian curves into a database, while the latter one records the frequency of each RSS value and constructs a RSS distribution histogram. In [20], Kaemarungsi studied the variations of RSS distributions with respect to the interference of device orientation and body and infrastructure shadowing. The results in [20] can help to examine the properties of RSS fingerprints.

Besides neighbor matching and Bayesian estimation algorithms, pattern matching algorithm can also be used for fingerprint-based Wi-Fi localization. With the help of topological counter propagation network (CPN) and k-nearest neighborhood vector mapping, LENSR [34] can not only improve location speed, but also reduce computation cost. Similar work can be found in [35–37]. In [35], Outemzabet used particle filtering to enhance the accuracy of artificial neural network (ANN) based location system which is mounted with a digital compass. A compass and particle filtering approach are applied to avoid trajectory discontinuity and modify motion orientation respectively. In [36], the targets location is estimated by using a modular multi-layer perceptron (MMLP) which contains five key steps: RSS recording and outlier filtering, data normalization, neural network training, data post processing, and regression analysis to conduct location estimation. Different from LENSR and MMLP, a discriminant-adaptive neural network (DANN) is introduced in [37] to extract the most useful information into discriminative components for neural network training. In DANN, since most of the redundant information is discarded before neural network training, the localization accuracy and real-time capability are improved. In all, the training process is recognized as one of the most challenging parts for the better design of pattern matching based localization algorithm.

3.2 TOA and AOA-Based Localization

TOA and AOA-based localization are with the ideas of trilateration and triangulation algorithms. To enable the localization in 2-dimensional domain, the propagation time and arrival angles from 3 and 2 APs to the target are used for TOA and AOA-based localization respectively [38–40].

In TOA-based localization [38], by assuming that the propagation time is directly proportional to the distance, we apply trilateration algorithm to estimate the targets locations based on the distances from 3 APs to the target. These distances are calculated from the measured propagation time.

We should not only guarantee the precise time synchronization between APs and receiver, but also label the transmitting signal by the exact timestamps for the sake of precisely calculating the distances the signal has traveled. In concrete terms, the estimated location is determined by the hyperbolic curve which has the constant difference in signal arrival time from each pair of APs [39].

The two key advantages of AOA-based localization are that there are as few as 2 APs for 2-dimensional localization, and meanwhile the time synchronization is not required [40]. The localization accuracy could be seriously deteriorated when the signal is blocked by the walls or the target is significantly far away from APs. In all, TOA and AOA-based location systems involve substantial changes of both APs and receivers.

3.3 Propagation Model-Based Localization

As discussed in [41], the mean of RSS decreases logarithmically with the increase of the distance between AP and receiver in ideal space. If the small-scale fading dominants over the large-scale fading or the propagation models are not predicted precisely, the accuracy of propagation model-based localization could be degraded. Ahn [42] studied the integration of Wi-Fi, UWB, and ZigBee technologies for indoor localization and introduced a new way to the prediction of finer propagation model corresponding to the target domain by using an iterative model modification process.

Narzullaev [43] compared the performance of three representative propagation models: (1) log-distance model which is based on the assumption that the mean of RSS varies logarithmically with respect to the propagation distance; (2) multi-slope model which gives better estimation of RSS distributions and saves the effort for RSS recording; and (3) multi-wall model which provides the finest prediction of RSS in indoor environments. More studies on propagation model-based Wi-Fi localization can be found in [44,45]. Finally, Table 2 briefly

Table 2. Comparison of several indoor location solutions

Solutions	Algorithms	Accuracy	Main cost	Availability
RADAR [17]	KNN and Viterbi-like enhanced KNN	4 m within 50% by KNN;2.37 m–2.65 m within 50% and 5.93 m–5.97 m within 90% by Viterbi-like enhanced KNN	Traversal of radio map to find the nearest neighbor(s)	On the same floor in a 3-storey building with dimensions of 43.5 m by 22.5 m and all the 70 RPs calibrated in linear corridors
Horus [32]	Bayesian estimation	2.1m within more than 90%	Small-scale compensation	On the fourth floor in a building with dimensions of 68.2 m by 25.9 m and 110 RPs and 62 RPs calibrated in linear corridors and rooms
Nibble [33]	Bayesian estimation	97% accuracy by using all APs and 96% accuracy by using 3 neighboring APs	Recording of the frequency the target is at a certain location and the updating of frequency	On the second floor in a building with dimensions of 224 by 9 feet including 40 offices, three clusters of cubicles, and several conference rooms
LENSR [34]	CPN with KNN	1 m within 90.6% and 1.5 m within 96.4%	Creation of the theoretical propagation model	Simulation environment with dimensions of 20 m by 20 m and all the RPs calibrated with the interval of 1 m
Outemz abet [35]	Enhanced ANN	39% and 50% accuracy improvement by using nonlinear and linearized filtering compared to Kalman filtering	Particle filtering	On the fifth floor in a building which has a trapezoidal shape with dimensions of 95 m, 70 m, and 40 m and all the 555 RPs calibrated in linear corridors
MMLP [36]	MMLP	0.1258 m error in average and the maximum error of 2.1667 m	Filtering of the timely nonregular patterns for neural network training	On the third floor in a building covering an area of 286 m^2 and 24 RPs and 39 RPs calibrated in linear corridors and rooms
DANN [37]	DANN	4 m within 88.6% and 2.5 m within 70.48%	Extraction of the most useful information into discriminative components for neural network training	On the same floor in a building with dimensions of 24.6 m by 17.6 m and all the 45 RPs calibrated in linear corridors with the interval of about 2 m
TOA [38]	Trilateration	Average root-mean-square error (RMSE) of 1.1 m	Precise time synchronization between APs and receiver	In a linear corridor with an AP mounted on one end of the corridor and the RPs calibrated at 2 m increments
Ahn [42]	Propagation model	Most of the errors falling into the range of [2 m, 4 m]	Integration of Wi-Fi, UWB, and ZigBee technologies	In an office with 5 reference transmitters and mobile reference tags fixed 3 m height
Narzullaev [43]	Propagation model	Average error of 5.9 m, 5.3 m within 50%, 7.3 m within 67%, and 9.6 m within 90%	Optimization of calibration procedure	In an office with dimensions of 18 m by 12 m and 51 RPs calibrated in a 2 m-grid

compares the previously mentioned location solutions in terms of algorithms, accuracy, main cost, and availability.

4 Conclusion

In this paper, we have reviewed and studied several comparisons of the computations to improve the distance dependency of Wi-Fi RSS fingerprints and enhance the location accuracy of neighbor matching and Bayesian estimation for Wi-Fi localization. Because it is cannot work well in urban and indoor environment due to the poor quality of RSS received from satellites. There are three typical categories of Wi-Fi localization algorithms: RSS fingerprint-based, time of arrival (TOA) and angle of arrival (AOA)-based, and propagation model-based localization. In this paper can be considered of localization accuracy and computation and maintenance cost, RSS fingerprint-based indoor Wi-Fi localization algorithm is preferred. The major contribution of this paper is that based on autocorrelation property of the real Wi-Fi RSS sequences, we present to eliminate the unstable RSS samples which are much likely to be interfered by burst noise. A reliable approach to be used to detect the existence of burst noise in each RSS sequence forms another interesting direction.

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