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Modern WLAN Fingerprinting Indoor Positioning Methods and Deployment Challenges

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Abstract: *Wireless Local Area Networks (WLANs) have become a promising choice for indoor positioning as the only existing and established infrastructure, to localize mobile and stationary users indoors. However, since WLANs have been initially designed for wireless networking and not positioning, the localization task based on WLAN signals has several challenges. Amongst the WLAN positioning methods, WLAN fingerprinting localization has recently garnered great attention due to its promising performance. Notwithstanding, WLAN fingerprinting faces several challenges. This paper consists of three main parts: 1) Conventional localization schemes; 2) state-of-the-art approaches, and 3) practical deployment challenges. , we compare some of the representative localization schemes in a single real environment and assess their localization accuracy, positioning error statistics, and complexity. Our results depict an illustrative evaluation of the approaches in the literature and guide to future improvement opportunities.*

Keywords: Indoor positioning, WLAN fingerprinting, real-time processing, clustering, sparse recovery, outlier detection

I. Introduction

LOCATION-based services (LBSs) have become the main niche for future applications and strongly drive the development of location determination technologies. and enable other applications. While the US Global Positioning System (GPS) and other similar global navigation satellite systems (GNSS) provide good quality for outdoor positioning robust indoor positioning is still an open problem. The GPS and similar localization networks do not work indoors as they need a direct Line of Sight (LOS) between the satellites and the user, which is not applicable indoors as shown in Fig. 1.

Various techniques have been proposed for indoor positioning. From a signaling perspective these approaches can be divided into two categories (1) radio-based positioning such as Radio Frequency (RF) proximity sensorsalso called Radio Frequency Identification (RFID), Ultra Wide Band (UWB) methods Bluetooth-based methods, ZigBee-based methods, Frequency Modulation (FM)

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Methods: Wireless Local Area Network (WLAN) methods; and (2) no radio-based positioning methods which utilize infrared (IR) ultrasonic and sound techniques visible light. 802.11b/g). Since these bands are unlicensed, several networks may transmit simultaneously and coexist with some interference.

1.1 Indoor Localization Approaches

Historically, from the position computation perspective of radio-based signaling systems, the known approaches for WLAN positioning are of three main categories: (1) Angle of Arrival (AOA) and related Direction of Arrival (DOA) methods; (2) Time of Arrival (TOA) and related Time Difference of Arrival (TDOA) techniques; and (3) RSS exploitation methods (fingerprinting). These methods are shown in Fig. 2 and are reviewed next.

In AOA, the angle between the incident wave and a reference direction, known as orientation, is measured from at least two Access Points (APs). The APs are equipped with an antenna array capable of determining the angle of the received signal. The intersection of the two virtual lines heading in the direction of the angles defines the user position.

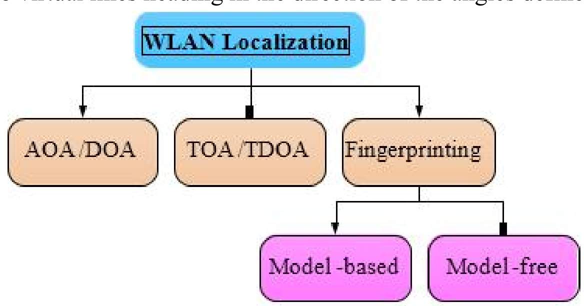

Figure 2: WLAN localization schemes.

TOA techniques use the travel time of a wave from the transmitter to the receiver and transform it to range distance. At least three APs measure the TOA from a mobile device. Trilateration is applied for this positioning technique [37], [46]. In trilateration, the APs coordinates are known. Considering an AP as the locus, the range distance defines a circle of certain radius. The intersection of these circles associated with several loci allows to estimate the user's position. However, there is a great probability that the circles do not intersect precisely at a point due to noisy measurements and the position is estimated with a limited accuracy. The localization based on TOA is shown in Fig. 3. To find the user's location, the following non-linear system of equations should be solved

$$r_i = d_i + \epsilon_i = \sqrt{(x_i - x)^2 + (y_i - y)^2} + \epsilon_i$$
$$i = 1, \ldots, N$$

where r_i is the range distance computed from TOA, d_i is the true distance, and $_i$ is the corresponding noise, $\mathbf{p} = (x,y)$ is the user's location to be estimated, and $\mathbf{p}_i = (x_i, y_i)$ is the i-th AP location. As illustrated in Fig. 3, due to the range measurement noise, the location of the user cannot be computed exactly and more sophisticated algorithms that minimize the mean square error (MSE), such as least squares (LS), are applied.

TDOA is a variation of TOA, in which a source signal is selected and the time difference of arrival between several spatially distributed APs is measured with respect to the source signal. Since the signal is received from several APs, the location of the user is defined through the intersection of hyperboloids whose radii is the distance between APs and the user [47], [48].

The above approaches need AP-user LOS. Although some enhancements have been proposed for non-LOS (NLOS) conditions [49], [50], the localization errors are high. In addition, the locations of the APs should also be known. These are not generally available and might be subject to change for the purpose of providing maximum network coverage.

WLAN fingerprinting methods, which use the Received Signal Strength (RSS), i.e., the power of received signals from WLAN APs, have recently captured a lot of attention. The reasons are two-fold: 1) WLANs are widely deployed in offices, business buildings, shopping malls, airports, home environments, etc., and provide ubiquitous area coverage. 2) The mobile and wireless receivers all contain Network.

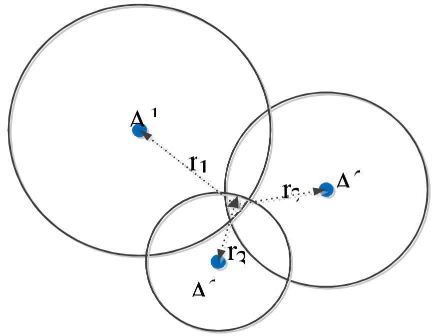

Figure 3: Localization based on TOA.

Interface Cards (NICs) to provide RSS measurements. Thus, there is no need to install any additional hardware, leading to a reduction in infrastructure installation, as well as equipment and labor costs. NICs are usually able to capture distinct RSS magnitudes at a rate of either 0.5 or 1 samples per second.

In general, the RSS exploitation approaches are divided into two broad categories: *model-based (path loss)* and *model-free (radio map)* approaches.

The model-based approaches use the collected RSS fingerprints to train the parameters of predefined propagation models. These techniques assume a path loss model for the indoor propagation which is a logarithmic decay function of the distance from the AP as

$$PL = PL_0 + 10\gamma \log_{10}\frac{d}{d_0} \quad (2)$$

where *PL* is the path loss measured in dB, *d* is the length of the path, d_0 is the reference distance, and γ is the path loss coefficient. Using the collected RSS and the path loss model, the distance *d* between the AP and the user is computed. Then, the location of the user is estimated using the trilateration. To render a more accurate modeling and decrease the discrepancy between the RSS measurements and the model, a random component is added to compensate for the RSS variations [54]. However, the asymmetric structure of indoor environments requires different path loss coefficients in different directions.

The radio map based techniques, also called *fingerprinting techniques*, make the use of dense AP deployments in indoor areas. A set of RSS or other measurements serve as a fingerprint which should be more or less unique for each location. In most cases, WLAN fingerprinting consists of *offline* and *online* phases. A schematic of typical WLAN fingerprinting localization is depicted in Fig. 4.

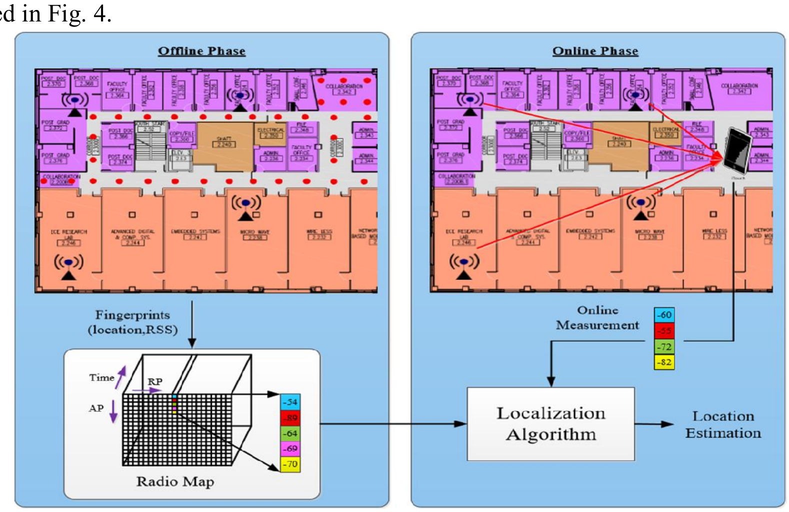

Figure 4: The typical illustration of indoor WLAN fingerprinting localization system.

First of all, a set of predefined points, referred to as *Reference Points* (RPs), also called landmarks, grid, or survey points, are selected. These terms are used interchangeably throughout this paper. During the offline phase, a survey is conducted and multiple copies of RSS measurements are read at each RP from available APs throughout a time interval. The database of fingerprints for all RPs constitutes a *radio map* for the whole area. Then, during the online phase, the user observes RSS

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measurements at his location and applies algorithms to associate these measurements to the radio map entries by finding similar fingerprints, and using the associated RP locations for estimating the user's position. A combination of TOA and fingerprinting has also been introduced. For a signal level that the user receives from an AP, it forms a contour consisting of all the RPs of the same signal level for that AP. The user's location is estimated as the juncture of all the contours, following the spirit of trilateration.

Fingerprinting emerges as a straightforward and plausible alternative, offering both accuracy and ubiquity. Typically, radio map methods do not need to know AP locations, no LOS requirements, and render superior localization accuracy, which makes it remarkable over other methods.

1.2 High-level Categorization of Fingerprinting Methods

A summary of fingerprinting categorization methods is provided in Fig. 5. WLAN fingerprinting methods differ in computational requirements. Since the computational complexity of advanced indoor localization systems is high, some implementations delegate computational and data-keeping tasks to remote high-performance servers. This is referred to as server-based localization from an implementation perspective. The servers can keep large radio map and navigation-map databases as well. In client-based implementations, location computations and navigation tasks are performed on resourcelimited hand-held wireless devices. The devices should also store large radio map data. While client-based approaches are attractive from an autonomous operation perspective and do not rely on server supports, they need to minimize the computational complexity of the localization process and have extended memory.

More balanced implementation approaches employ hybrid techniques, by estimating a coarse location of the user on a larger area first and then refining it on a smaller scale. This way, the device needs to load part of the radio map. The approaches for coarse localization are elaborated in Section III. Client-based methods are sometimes considered more preferable for users as privacy issues are typically associated with the server-based techniques. Without loss of generality, clientbased approaches are considered in the following.

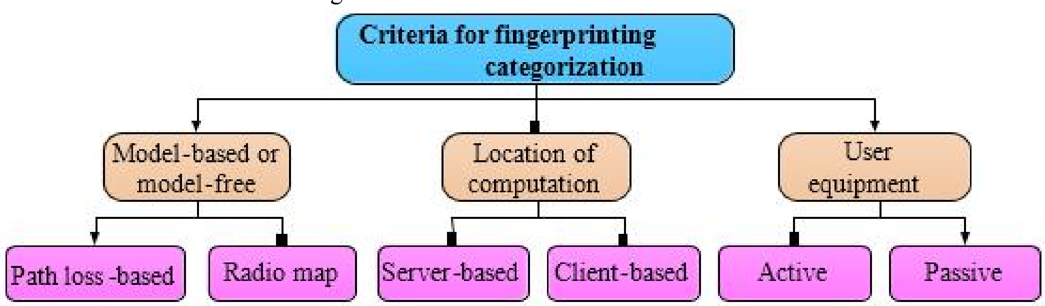

Figure 5: Different criteria for the categorization of fingerprinting localization approaches.

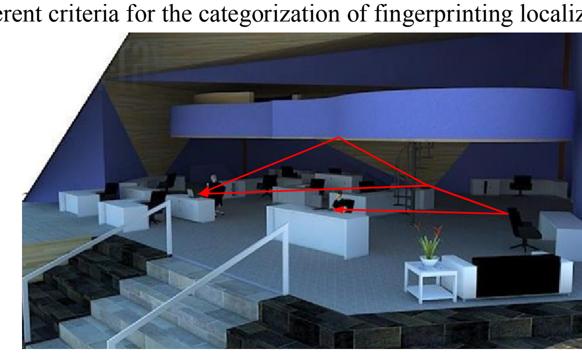

Figure 6: The multipath profile of the WLAN signals is a major problem for localization.

In general, fingerprinting localization requires the user to carry a wireless device such as a laptop, tablet, and smartphone. These devices capture the RSS measurements for the localizations. However, some recent methods do not require the user to carry any device and are known as *passive (device-free) localization*. In passive localization, RSS measurements are taken from wireless devices available in the area which basically measure the changes in RSS profile in the presence of the user at different positions. The passive methods are not discussed in this paper.

1.3 Fingerprinting Localization Challenges

WLAN fingerprinting localization schemes face several challenges. RSS measurements are distorted by shadowing and NLOS propagation due to the presence of walls, doors, furniture, objects, and humans. Fig. 6 shows a typical office environment and wireless router signals which travel different paths to the wireless devices. So, the propagated signal is affected by severe frequency selective multipath fluctuations and hence cannot be considered wide sense stationary (non-WSS). Moreover, WLANs operate on unlicensed frequencies of 2.4GHz and 5GHz, which are open to cordless phones and microwaves, and include the resonance frequency of water. These band characteristics lead to interference from such devices and signal absorption by the human body. These phenomena make RSS densities nonGaussian and time varying and complicates the RSS density estimation. For example, the use of mean and variance of a multimodal distribution may ignore important information that is helpful for discriminating among different locations. In addition, there are various WLANs in a typical area which add extra interference among each other. Also, it is possible that the wireless network coverage degrades due to AP failures [66], [67].

Table 1: Paper Organization And Contents

Part I	Section II: WLAN Fingerprinting Localization: Problem Formulation and Conventional Approaches	Discusses the fundamental concepts and the early fingerprinting approaches
Part II	Section III: RP Clustering	Restricts the localization into a sub-region
	Section IV: Exploitation of APs	Utilizes a suitable subset of APs
	Section V: Advanced Density and Weight Estimation Methods	Exploits representative features of the data
	Section VI: Sparsity-based Localization	Reformulates the WLAN localization to a sparse recovery problem
	Section VII: Assisted Localization	Employs available sensors in the environment and mounted sensors on the device
Part III	Section VIII: Radio Map Construction	Discusses methods of collecting fingerprints
	Section IX: Outlier Detection	Accounts for the possible outliers in the measurements
	Section X: Heterogeneous Devices	Considers the differences between fingerprinting and localization devices

There are also logistical problems in fingerprinting WLAN localization. First of all, the surveying stage is very time consuming as the surveyor needs to carry the recording device to each RP and record the RSS for a time period. Since including the whole set of RPs in the localization procedure increases the complexity, pre-processing techniques are usually employed to reduce the search area of the user location to a smaller region. The smaller region is usually selected by clustering the area. This eliminates the need for a comparison of the online measured RSS with all the RPs fingerprints and hence, the complexity decreases significantly. In the online phase, a subset of RSS measurements should be selected as not all measurements provide beneficial information. Additionally, not all APs provide valuable information for localization and some may lead to biased location estimation. So, an assessment of measurement sanity is conducted and a subset of APs is selected for positioning. An elaborate discussion on these methods are provided in this paper.

1.4 What This Paper Brings to the Scene

Wireless indoor localization has been previously reviewed. Though providing a detailed review, most of the previous surveys did not comprehensively cover finer aspects addressed in various fingerprinting localization systems. It is common for them to address state-of-the-art at very high abstraction levels. Moreover, the research volume of fingerprinting and related localization approaches has increased extensively in recent years, and many new methods employ advanced theoretical concepts that need at least concise mathematical formulations for review-style coverages. Meanwhile, most of the referenced surveys have discussed the current fingerprinting localization approaches generally and did not dig into technical aspects. The readers are encouraged to review these publications first if they expect very general coverage, as this paper reviews advanced concepts in more detail and employs minimalistic mathematical background that allows addressing concisely advanced concepts and practical implementation intricacies.

Also, various studies use different mathematical notations which complicate relative association of similar concepts. This review employs unified notation for more simplified representation for the readers.

In sum, our paper addresses the problem from a different perspective. In particular: (a) a unified formal description is included which will help the readers to grasp common notation practice in the area; (b) various reported methods of coarse-fine localization steps and AP selection are discussed; (c) recently reported approaches on applying sparse recovery methods on WLAN localization are surveyed; (d) outlier detection methods are reviewed; (e) radio map interpolation schemes are elaborated; and (f) technical comparisons over the representative methods are discussed.

The discussion in this paper is divided into three main parts which are overviewed next. Table I lists the related sections and contents of each part:

1. Conventional Approaches and Problem Formulation (Section II): In this part, we discuss the fundamental fingerprinting concepts and unify the different notations used in the literature. Then, the conventional approaches, which have been proposed in the early stages of WiFi based localization, are organized in three general categories.
2. State-of-the-Art Approaches: The wide variety of recent trends toward Wi-Fi based localization can be organized along the following paths:
    a. Refinements of the Conventional Localization: Since the conventional methods cannot achieve the necessary localization accuracy and the online running time cannot pace with the user's motion, refinements have been introduced. These have focused on RP clustering (Section III), exploitation of APs (Section IV), and advanced density and weight estimation methods (Section V). These techniques are direct modifications of the conventional approaches.
    b. Sparsity-based Localization (Section VI): A reformulation of WLAN localization has been recently introduced which exploits sparse recovery methods.
    c. Assisted Localization (Section VII): Aside from merely utilizing WLAN fingerprints for localization, some methods gain assistance from available resources in the environment and user's device to achieve superior localization accuracy. These methods may integrate sensory signatures built in the modern wireless devices, track the user's motion, exploit the available environment landmarks, or utilize the peer-to-peer collaboration between devices, and collectively fall under assisted localization.
3. Deployment Challenges: Localization schemes face laborious deployment challenges which constraint their applicability as real positioning systems. Even with advanced localization techniques, practical systems should account for several challenges listed next.
    a. Radio map Construction (Section VIII): An existing problem with fingerprinting methods is the need for dense survey of the area. Previous works attempt to decrease the time and cost of fingerprinting tasks through crowd-sourcing, implicit or unlabeled data collection, and radio map interpolation.
    b. Outlier Detection (Section IX): APs are easily prone to infrastructure problems that render faulty readings. These faulty readings are called outliers. Outliers can occur both on fingerprints during the survey process and more importantly during the online phase. The fingerprint outliers are easier to detect. The presence of outliers during the online phase implies that the user's location should be estimated using faulty measurements.
    c. Heterogeneous Devices (Section X): Wireless devices obtain RSS fingerprints through their Network Interface Cards (NICs). The sensitivity of the wireless devices differ as the NICs chipsets are different and the position of the antenna on the device affects the RSS readings.

After the theoretical discussion, we provide a numerical evaluation of the representative approaches based on localization accuracy and positioning error statistics in Section XI. The methods are tested on the same set of fingerprints collected at the University of Texas at San Antonio (UTSA). These comparisons provide illustrative guidelines for future improvements. A critical summary and future directions are provided in Section XII.

1.5 Localization Error without Coarse Localization

The methods in this subsection have been implemented without utilizing any coarse localization. However, for reducing the number of APs, the Fisher criterion (27) has been applied. Fig. 13 illustrates the localization error versus an increasing number of APs. For the KNN method, K = 10 RPs have been selected. The kernel widths for KDE approach have been computed through the recommendations given in. The probability density of the RSS fingerprints had to be estimated in the online phase because the APs engaging in the localization should be known for the KDE approach. The GS approach needs the corresponding weight for each cluster which is computed through the layered clustering method (K = 10). The results show high localization errors for all approaches although the errors decrease as the number of APs increases. However, the sparse recovery methods show higher accuracy, among which the GS-based localization shows the least localization error if less than 10 AP are used. The GS accuracy slightly improves if more APs are used. Overall, LASSO-based localization shows the least localization error if more APs are used.

Fig. 12. The map of experimental environment. The green dots indicate the RP locations.

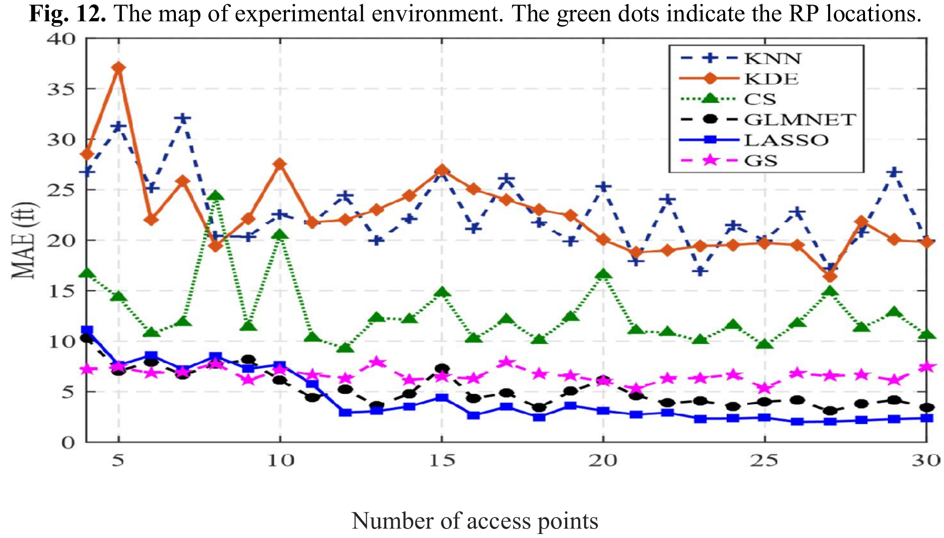

Fig. 13. Localization error comparison for different number of APs without clustering.

The localization error distribution is shown in Fig. 14 when 10 APs have been used for localization. The contour-based approach introduces the largest errors because it needs an estimation of the path loss parameters. These parameters are assumed uniform for an AP along all directions which is not a suitable assumption in complex indoor environments. The KNN and KDE techniques do not show satisfactory performance either.

1.6 Localization Error With Coarse Localization

As shown in the previous subsection, the localization accuracy is low without coarse localization in large surveying areas. To enhance the performance, the user's location is first estimated in the coarse localization stage, and the fine localization step is applied afterwards. To show that the localization accuracy is enhanced with coarse localization, the clustering using the AP coverage vector has been utilized for the KNN and KDE approaches as in [85], weighted clustering has been used for CS, LASSO, and GLMNET, and layered clustering has been used for GS.

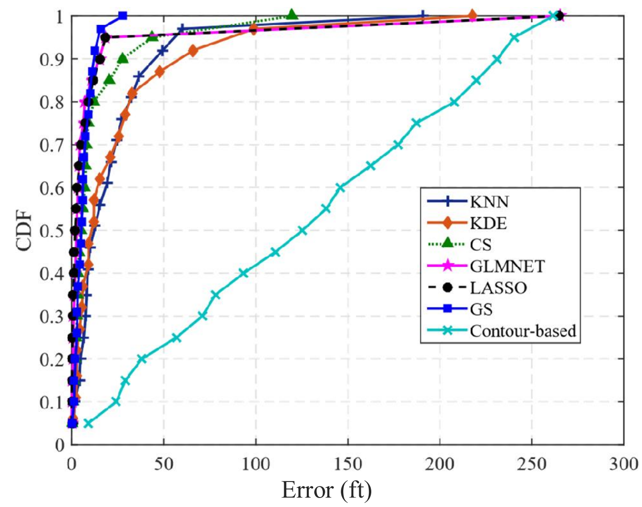

Fig. 14. The CDF of the localization error for 10 APs without clustering.

Fig. 15 shows the average localization error for an increasing number of APs. Increasing the number of AP slightly improves the KNN, KDE and GS approaches, however, the localization error decreases from 10 ft to 2 ft for LASSO and GLMNET if the number of engaged APs is increased from 4 to 29. However, it is evident that the localization error for CS, LASSO, and GLMNET has overall been decreased dramatically compared to when no coarse localization was used.

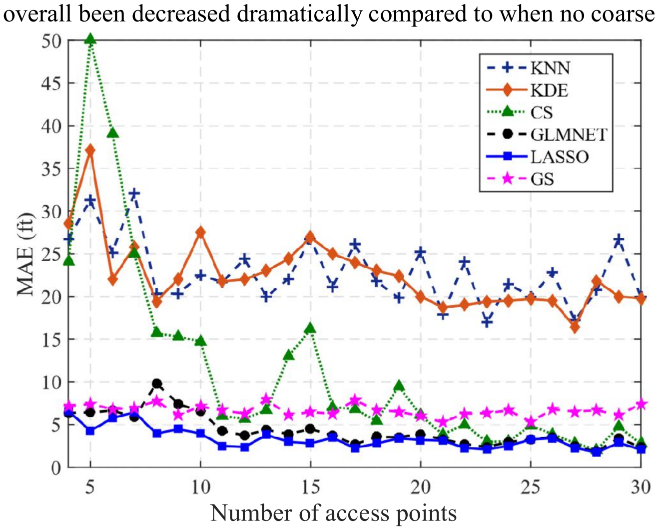

Fig. 15. Localization error comparison for different number of APs with clustering.

The distribution of the localization error is depicted in Fig. 16 when only 10 APs are utilized in localization. Comparing Figs. 16 and 14 reveals that the errors of CS, LASSO, and GLMNET are greatly decreased and the 80% of the errors are less than 20 ft. However, the KNN and KDE methods render unacceptably high localization errors.

1.7 Run-time Comparison

The percentiles of the position estimate errors are shown in Table VII for the implemented approaches. Considering the 50% percentile, the GLMNET and LASSO exhibit respectively 30% and 61% accuracy improvement relative to the CS method, and thus, outperform all others. The table also shows the running time of the online localization phase which conveys the computational efficiency of the methods. WKNN delivers the least running time. The GLMNET and LASSO, with 3.41 ms and 1.53 ms running times respectively, provide smaller localization errors compared to other methods but only GLMNET requires slightly longer running time.

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II. Critical Summary and Recommendations For Future Work

2.1 Critical Summary

WLAN indoor localization has attracted great attention due to the low cost deployment, existing infrastructure, and ease of implementation. The WLAN fingerprinting approach became very popular as proven performance was in real environments. Since indoor propagation is a very complex phenomenon distorted by multipath and signal blockages, conventional localization techniques did not show satisfactory performance. Hence, the subject has become very broad and extensively branched to address various challenges.

First, the paper categorizes conventional localization approaches at early stages. Then, the challenges that are associated with the fingerprinting approaches and conventional methods are enumerated. The state-of-the-art solutions to these challenges are categorized and the related works for each category has been overviewed. A key issue was to unify the misleading concepts and notations that varied among approaches and introduce them in a single tractable package. Recent approaches enhance the conventional methods, utilize the peculiarities of available environments and sensors, and leverage sparse recovery methods.

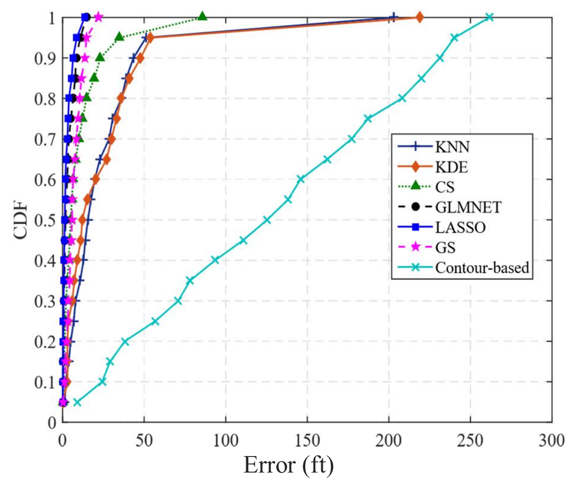

Fig. 16. The CDF of the localization error with 10 APs and clustering.

Since localization approaches in the literature have been evaluated in different settings, representative fingerprinting approaches are implemented in a typical office environment for illustration purposes. In parallel, the details of some of the fingerprinting approaches are listed in Table VIII which shows the RP clustering method, AP selection method, fine localization technique, reported accuracy and details about the implemented setting. The comparison over the reported accuracies is difficult as the methods have been implemented in different testbeds which differ in the size of the area, number of RPs, granularity of RPs, and number of training samples. It is also commonly understood that the RP clustering and AP selection schemes have great impact on improving the accuracy. A qualitative comparison over these methods is also provided in Table IX which describes the strengths and weaknesses of representative works.

In addition, if one compares the accuracy of approaches with coarser granularity, such as Tilejunction [87], the accuracy seems to be degraded compared to approaches with finer granularity. However, all methods should be implemented in a comparable granularity in order to extract safe conclusions. Therefore, comparison of many diverse localization techniques is hindered by the lack of standardized representative data that can be used for fair comparisons. In addition to the implementation results in Section XI, further analysis have been performed on another database obtained from BioScience and Engineering (BSE) building at the same university

2.2 Recommendations for Future Work

Emerging fields of Wi-Fi fingerprinting-based localization includes the following directions:

- The future practical localization approaches should greatly care about the multipath effects of the indoor fingerprints. The fingerprinting profile may include a multipath profile of fingerprints instead of time collection of single fingerprints. This needs the access to the physical layer of the wireless front-ends. As far as the authors know, the smart devices do not yet allow to this access due to security issues. The team is working on a software defined radio implementation that can provide such capability.

- The fingerprinting profile of an RP may also include the fingerprints of the user along with his trajectory. This associates a vector of the RSS to one RP and improves the available information in the system.

Localization approaches should care about the real environments performance when the infrastructure experiences intentional faults or in emergency scenarios when the navigation of people is of great importance.

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