Improving Multi-floor WiFi-based Indoor positioning systems by Fingerprint grouping

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Abstract. Wi-Fi fingerprinting indoor positioning systems (IPSs) have drawn a lot of attention due to their low Cap-Ex, but these systems suffer severe signal fluctuations which lead to accuracy reduction. In this paper Fingerprint (FP) grouping method is presented to improve Wi-Fi fingerprinting IPSs in multi-floor buildings. The proposed method consists of three sub-schemes. In each sub-scheme, FPs are grouped based on a different parameter, then in the online phase, the positioning algorithm is confined to specific FP groups determined by the method. Using this method, FPs which could reduce accuracy are filtered, and positioning is done on a subset of FP-database. In the first sub-scheme, FPs are grouped based on the received signal strength of Access Points (APs). In the second sub-scheme, fingerprint grouping is performed based on the last estimated location of the user. Fingerprint grouping based on the map-constrained graph, which is matched to the environment map, is the third sub-scheme. Not only these methods have improved the accuracy but also decreased the execution time spent in the positioning algorithm. The results of the practical tests indicate accuracy improvement of 6%, 47%, and 67% for each of the sub-schemes respectively and execution time reduction of 1.5 to 10 times.

Keywords: Multi-floor Indoor positioning, Wi-Fi Fingerprinting, Indoor maps.

1 Introduction

Internet of Things (IoT) has received a lot of attention recently, and location information has got an important role in many IoT scenarios. Therefore, it's necessary to have an appropriate positioning system for both indoor and outdoor environments. Specifically, indoor positioning can be used for building and security management, healthcare monitoring systems, indoor navigation, disaster management, and personalized location-based services for events and retail industry [1].

Nowadays the Global Positioning System (GPS) offers a great opportunity for estimating the position of things. Unfortunately, GPS doesn’t work properly indoors. So Indoor Positioning Systems (IPSs) are developed for this goal. By considering the fact that humans live most of their lives indoors, the importance of IPSs gets more significant.

Numerous technologies have been used for indoor positioning, either alone or in combination. These technologies include Radio signals (Wi-Fi, BLE, ZigBee, RFID, Ultra-Wideband), visible light, infra-red signals, and inertial motion sensors. Among these solutions, due to highly penetrated Wi-Fi networks in common buildings, Wi-Fi-based IPSs have been very popular in both research and industrial approaches. The most important reason for this popularity is the available infrastructure resulting in low implementation cost. On the other hand, Wi-Fi hasn't been developed for this goal in the first place, so it has numerous challenges. One of the most critical challenges is the fact that Wi-Fi has a lot of fluctuations in its signal. This challenge deteriorates when combined with the inherent complexity of indoor propagation of radio signals. Usage of radio signals including Wi-Fi for indoor positioning has been done in three major ways: Proximity, Triangulation or Trilateration, and Fingerprinting. The Third approach is now state-of-the-art due to its accuracy, however, this method faces the above challenges too.

Although most of the buildings are multi-floor nowadays, most of the research projects in the field have investigated single-floor environments. The importance of this issue comes from the fact that the mentioned challenges have a greater impact on the malfunction of the system in these environments. Related works that investigated this topic also used methods that did not apply to all devices.

In this paper, the fingerprint grouping (FP grouping) method is presented to improve Wi-Fi fingerprinting IPSs in multi-floor buildings. The proposed method consists of three sub-schemes that incrementally extend the grouping method.

In the first sub-scheme, fingerprints are simply grouped based on received signal strength (RSS) of Access Points (APs). In this sub-scheme, every FP is assigned to an AP if the RSS is larger than a Proximity Threshold (PT). Then in the online phase, the positioning algorithm considers only FP groups that meet the threshold based on RSSs received from each AP.

The second sub-scheme is based on the principle that a person has a certain velocity and he/she can't suddenly change his/her location to a distant point. Thus fingerprint grouping is performed based on the last estimated location of the user. It means, in every positioning phase, only FPs are used which are nearer to the last estimated location than a Max-Movement Threshold (MMT).

In the third sub-scheme, we looked at the subject more generally and used every feature of the building map. In this sub-scheme, Fingerprint grouping is based on the map-constrained graph which is matched to the map of the multi-floor environment.

The rest of the paper is organized as follows. Section 2 presents a brief explanation of past works. The proposed method is detailed in Section 3. The experiments and evaluations are reported in Section 4. Conclusions and future works are presented in Section 5.

2 Related work

In this section, the approaches to solving the positioning problem in multi-floor environments are described. Then, works related to fingerprints grouping are surveyed in the section named as coarse and fine localization. Finally, positioning methods using features of the building map are surveyed and categorized into two general groups, particle-filter methods and graph models.

2.1 Positioning in multi-floor environments

Most of the deployed IPSs are focusing on single-floor positioning, while the true determination of the floor is vital for an accurate positioning system. Those who consider multi-floor positioning are divided into two categories. The first category claims that using the fingerprinting approach itself can mitigate this problem [2–6], while the other category claims the fingerprinting insufficient by itself and proposes methods to solve the problem [7–11].

The first category mostly uses fingerprinting and Euclidean distance. In [3] a hierarchical Bayesian network and cellphone sensors are used. It is realized in [5] that radio map of different floors has a kind of similarity which enables producing it from a single floor and use it for other floors by some modifications. A Bayesian graphical model is designed in [4] and the positioning system is developed in a two-floor building. In [2] cellphone's sensors are used to determine the floor-change.

The second category generally determines the floor before the determination of an accurate position. In [9] nearest AP is determined by using KNN and according to that, the floor is recognized. [8] proposes a system based on cellular signals fingerprinting which helps emergency officers to arrive at the scene faster. In [11] a third coordinate is added to x and y coordinates which represents the floor. During the positioning phase, it localizes the person by calculating the Euclidean distance between the current RSS and the average of near Reference Points (RPs) on a floor. F-loc [12] just uses motion sensors to determine the floor while due to the difference among people's walking patterns, it has some problems. Some researches [13–16] propose methods to use cellphone barometers for floor determination. However, due to the lack of complete availability of these sensors in today's typical mobile phones, it needs considerable time to be widely applicable.

2.2 Coarse and Fine localization (FP clustering)

In some researches, the positioning is divided into two phases: Coarse and fine localization. This approach not only improves accuracy and precision but also reduces the computational load. In this approach, the full search space consisting of all of the RPs is divided into some subsets based on similarity. In the positioning process, firstly the coarse localization is performed, and the subset is determined which current RSS vector belongs to. After that, the fine localization is performed using only the FPs in the chosen subset. Obviously, this method has an offline phase too, in which the FP clustering is done based on a similarity parameter [17]. There are different ways to perform this clustering. AP-coverage is one of the similarity parameters used for clustering [18–20]. AP-coverage clustering is based on the fact that near RPs receive similar RSSs from similar APs. Another clustering method is the Dynamic Subarea method presented in [21]. In this method, the location estimated by motion sensors is used as the center, and only RPs around this estimated location is used in the positioning.

2.3 Using features of the building map

The idea of using topology and indoor maps has been widely explored recently. The basis of this idea is using the normal limits on people's moving caused by indoor walls, floors, etc. Contrary to most of the accuracy improvement methods, using indoor maps is independent of the indoor positioning technology. To implement this idea, related works used Particle Filter mostly. As seen in **Fig. 1**, map matching algorithms are divided into two approaches. In the first approach, map matching is performed by probabilistic methods based on particle filter using wall constraints. The second approach is map matching based on the Link-Node model of indoor maps.

Map-matching using wall constraints based on Particle Filter. These methods mostly use Particle Filter for implementing the idea [2, 22–25]. These algorithms use a set of weighted samples named particles which shows the density of next locations in

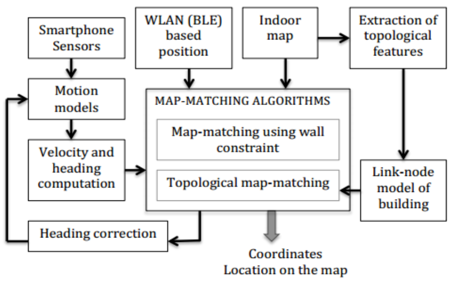


Fig. 1. Categorization of methods for using indoor maps in positioning [26]

localization. Walls are constraints on the map that particles can't pass through them, and if one did, it would be omitted from the next estimations. This type of limitation is prevalent in the literature. The way that particles propagate, the method for updating each particle's weight, and the determination of data or sensors used for smart dispersing them are differentiators among different researches. These methods generally suffer from a high computational load.

Topological Map Matching via Link-Node model (Graph). Many researchers matched links and nodes (Graph) on indoor maps similar to streets in outdoor maps. In these representations, a node is known by its coordinates, and a link connects two nodes as an edge. This model also helps in implementing navigation services, because most of the navigation algorithms are defined using graph data structure [27]. After this map matching, different algorithms are used to improve the positioning process. Some of them are based on Particle Filters [28–31]. These methods use the constraints of moving around the environment as additional information, as moving is allowed only around and in line with the edges of the graph. In addition to Particle Filter, there are some other methods too. In [32] edges are named as path segments and instead of RPs, these path segments are used for positioning. The method presented in [33] and [34] doesn't use the graph but defines a parameter named Route Probability Factor (RPF). This factor is multiplied by the weights of RPs in WKNN to improve positioning. The statistics of common passing routes determine this factor, so it implicitly uses moving constraints, for example, it approaches zero around the walls while has a high value in the middle of corridors.

2.4 Conclusion of Related works

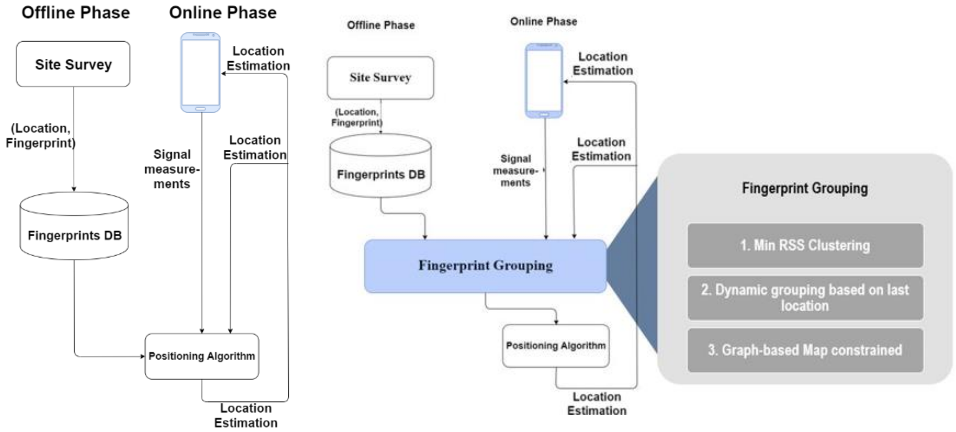
In this section, works related to proposed methods were surveyed. A summary is presented in **Table 1**. As inferred, none of the presented solutions is the panacea and some of them suffer from serious deficiencies too. In the scope of Multi-floor positioning, based on authors' experiments, despite reports in [2–6], fingerprinting itself can't solve the problem. Also, using extra sensors such as barometers and motion sensors like [6–15] causes new restrictions on the system. These restrictions include the topology of the system and also, the fact that all users must have required sensors on their mobile phones. In the scope of using map features in positioning, each solution has its pros and cons. In other words, each of them proposes some new ideas but has problems such as complexity load and not considering multi-floor environments. This paper proposes schemes that improve Multi-floor indoor positioning without using extra sensors.

Table 1. Summary of Related works

Scope		**Related works**
Positioning in Multi-floor environments	Sufficiency of fingerprinting	[2–6]
	Using extra sensors such as Motion sensors, Barometer, etc.	[6–15]
Coarse and Fine localization (FP clustering)	AP Coverage	[16–19]
	Dynamic Subarea Method	[20]
Using features of the building map	Map-Matching using wall constraints based on Particle Filter	[2, 22–25]
	Topological Map Matching via Link-Node model (Graph)	[26–33]

3 Proposed Methods

Among the three major methods of indoor positioning, namely: Proximity, Triangulation or Trilateration, and Fingerprinting, this paper uses the third one. This method, depicted in **Fig. 2. a**, consists of two phases. The first phase, which is offline, is the site survey. In this phase, the radio map of the environment is produced by recording different RPs and respective RSS vectors. In the second phase, which is online, the mobile phone sends its received RSS vector at arbitrary intervals. At the positioning server, this RSS vector (y) is compared to the all N RSS vectors in the radio map database (r_j) and calculates its Euclidean distance ($d(r_j, y)$) from the RSS vector of each of RPs.



(a) Classic Fingerprinting system flow

(b) Proposed FP Grouping method flow

Fig. 2. Fingerprint Grouping relation to the whole positioning process

Then inverse of these distances are used as weights (w_j) in the WKNN (Weighted K-Nearest Neighbors) algorith. In this algorithm, the location (l_{WKNN}) is estimated by the weighted average of K nearest matches.

$$d(r_j, y) = \| y - r_j \|_2 \qquad j = 1, \dots, N \tag{1}$$

$$w(j) = \frac{1}{d(r_j, y)} \qquad j = 1, \dots, N \tag{2}$$

$$l_{WKNN} = \sum_{j \in K} \frac{w_j}{\sum_{j \in K} w_j} l_j \tag{3}$$

After implementation, by considering the pattern of frequent errors, the idea of using some parameters came to mind. Some parameters which aren't deployed normally while they don't need any extra sensors. These parameters include environmental constraints such as walls and floors, AP proximity and the fact that a person can't move a long distance in a short time.

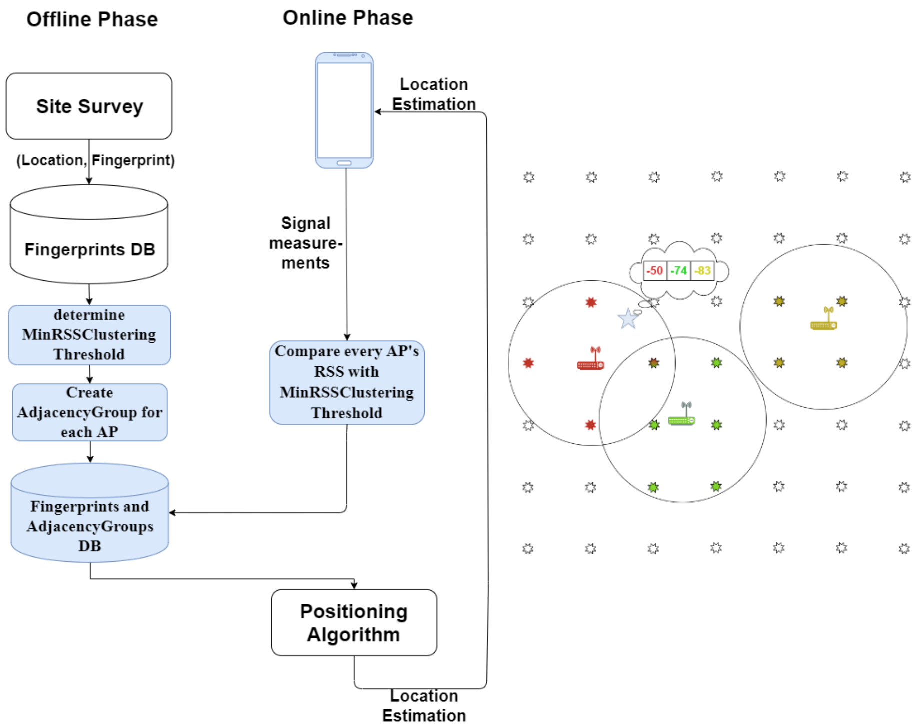
Fingerprints are grouped based on these parameters, and the Fingerprint Grouping method is proposed and integrated into traditional fingerprinting systems. As seen in **Fig. 2**, Fingerprint Grouping is present at both offline and online phases. In the offline phase, the fingerprints are grouped according to a criterion that is specified in each sub-scheme. Then in the online phase, the proposed method is to select the appropriate group of fingerprints first and then use only the same group of fingerprints for positioning. As such, fingerprints that may increase the error are not used in the positioning algorithm. In addition, by limiting the set of fingerprints used in the algorithm, the execution time is reduced.

The criterion on which grouping is based is a very important and challenging subject. This criterion is the differentiator among the 3 proposed sub-schemes. As mentioned earlier, each sub-scheme proposes a criterion and related thresholds which obviously should get chosen wisely. The criterion in the first sub-scheme is the proximity of APs. The second sub-scheme uses the proximity of the user's last location as the criterion. The third sub-scheme extends the latter idea and applies the natural constraints on the environment map such as walls and floors. In other words, one cannot not only move momentarily from one place to a distant spot but also cannot cross a wall or move to another floor without the use of elevators and stairs.

3.1 Min RSS Clustering

A data that is not being appropriately used in the classic KNN algorithm is a strong RSS which can represent the proximity of an AP. This data can exclude a lot of RPs from inputs of the positioning algorithm and leads to reducing the computational cost. On the other hand, it improves positioning accuracy by filtering the RPs which are physically far, but because of Wi-Fi signal fluctuations, got a low Euclidean distance.

This sub-scheme illustrated at part (a) of **Fig. 3**. In the offline phase, every RP is assigned to one or more APs which its RSS from them is stronger than *MinRSSClusteringThreshold*. This assignment of RPs to APs is done like **Fig. 3. (b)**. The *MinRSSClusteringThreshold* is determined using leave-one-out-cross-validation over RSS vectors in the radio map database, such that by setting the threshold and then choosing each RSS vector as a positioning RSS, the chosen threshold presents a minimum sum of error.



(a) Flowchart of Fingerprint-based IPS improved by 1st sub-scheme (steps added by the proposed method are represented by blue shapes)

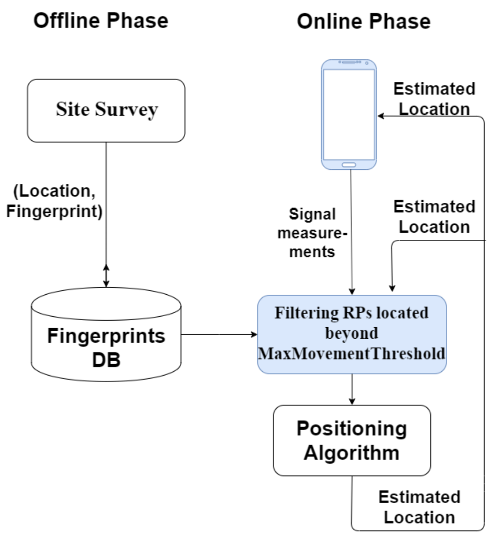
(b) A sample of RSS vector from different APs for a point is shown. (Circles, represents AP Coverage and RPs are represented by stars)

Fig. 3. Min RSS Clustering

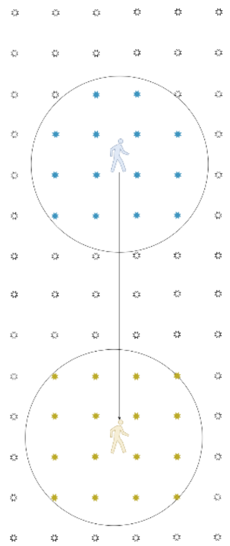
In the online phase, each RSS is compared to the *MinRSSClusteringThreshold*. If RSS from an AP is greater than the threshold, the FPs of the AP(s) cluster(s) are loaded and used. Otherwise, if the RSS didn't meet any threshold of APs, all of the fingerprints in the radio map database are used in WKNN for positioning. Although this sub-scheme acknowledged the idea of grouping, it did not provide much improvement, especially in reducing floor errors.

3.2 Dynamic Grouping based on the Last Location

During numerous experiments, it was observed that sometimes two vectors of RSSs, although physically located at very distant points, have a small Euclidean distance. To reduce the error caused by that, the impossibility of moving a far distance in a limited time can be very helpful. It can be named as locality. It appears to be very important because using the classic implementation of WKNN positioning algorithm, especially in environments with a low density of APs; the mentioned similarity causes errors as leaps in the positioning map. To mitigate this problem, the current sub-scheme is proposed. In this method, only the RPs are used in positioning algorithm which are nearer than a threshold from the last estimated location. In this way, the FPs used in positioning are dynamically changed as shown in part (b) of **Fig. 4**. The mentioned threshold named *MaxMovementThreshold* is determined in the offline phase using experiments on different walking tracks with different thresholds.



(a) Flowchart of Fingerprint-based IPS improved by 2nd sub-scheme (steps added by the proposed method are represented by blue shapes)



(b) An example of a user's movement in the environment and reference points involved in the online phase for positioning. (Circles, represents *MaxMovementThreshold* and RPs are represented by stars)

Fig. 4. Dynamic grouping based on last estimated location

3.3 Graph-based Map-Constrained Grouping

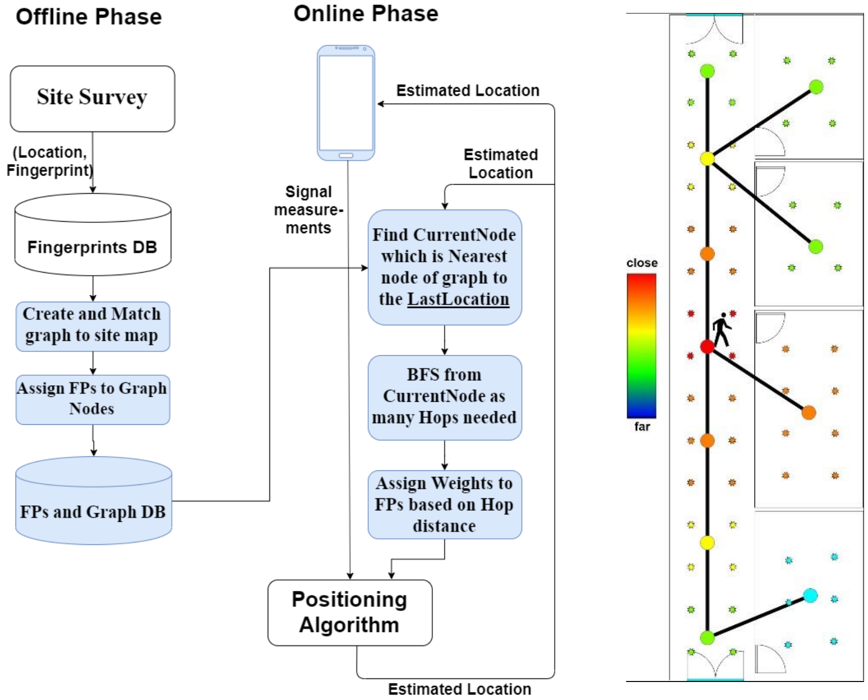
To extend the fingerprint grouping idea by using smarter criteria, map constraints were investigated. In the positioning using WKNN, environments' constraints such as walls, floors, etc. aren't considered at all. As a result, errors between floors or passing walls or leaps to another side of the building aren't rare, so it seems essential to solving such problems.

While the last two sub-schemes performed well at mitigation of errors especially the far ones, but they don't help so much on solving multi-floor and topological errors. The reason for the first sub-scheme is that it doesn't have any idea which floor does the strongest AP reside thus it can't help. The second sub-scheme performs based on Euclidean distance on the map so it can help neither on floor errors nor topological errors.

The first step to implement Graph-based Map-Constrained Grouping is to match a graph to the map of the environment in a way that:

- There is at least a node in every room or hall to represent the RPs in that proximity.
- Edges are fixed in a way that they describe the passing routes.

- Preferably length of the edges should be equal.



(a) Flowchart of Fingerprint-based IPS improved by 3rd sub-scheme (steps added by the proposed method are represented by blue shapes)

(b) An example of using a graph to limit the reference points involved in positioning. (stars represent RPs and circle-points represent Graph Nodes)

Fig. 5. Graph-based Map-Constrained Grouping

Afterward, every RP is assigned to the nearest graph node (as shown in **Fig. 5. b**).

In the online phase, in every positioning interval, the nearest node to the last estimated location is set as a current node and root of Breadth-First Search (BFS). Based on this search and the distance of each node to the current node, a factor is multiplied to FPs' weight in the WKNN algorithm. As it seems rational, this factor has its highest value for current and near nodes and becomes less when the distance becomes more, in a way that at a distance, finally it is set to zero. The best values for these parameters are different based on application, environment, and distance between graph nodes. They can be set experimentally for each environment by a limited count of experiments. The flowchart of this sub-scheme is presented in **Fig. 5. a**.

4 Evaluation

4.1 The topology of the implemented Indoor Positioning System

The system consists of a mobile application and a positioning server. The mobile application is used for both offline site surveys and online positioning. It receives and integrates RSSs from APs and sends them to the positioning server via the cellular network. The reason for choosing cellular networks is that when a mobile phone connected to an AP, the received signal fluctuations from the AP aren't equal to when not connected and that could affect the accuracy of positioning. The topology of the system is presented in **Fig. 6. a**.

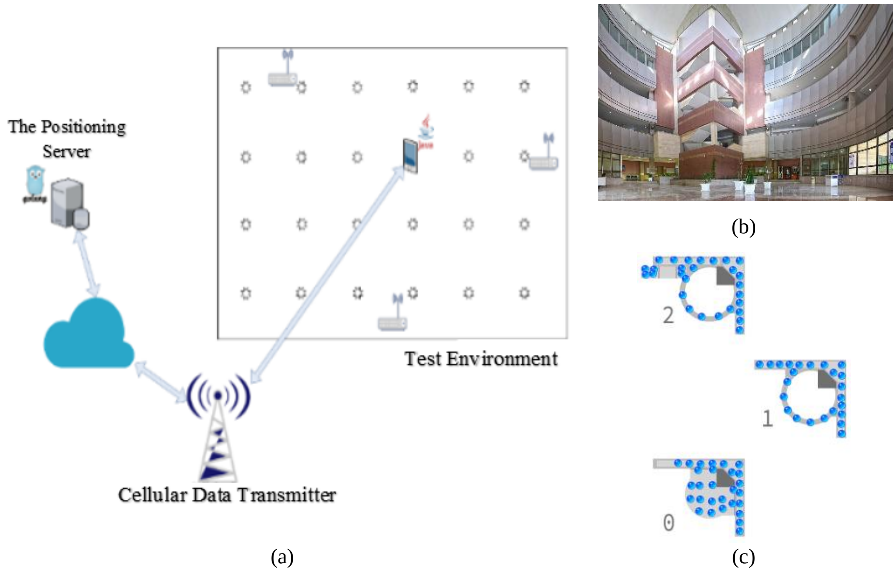


Fig. 6. (a) Topology of the implemented IPS (b) A view of CE faculty of IUST (test environment) (c) Map of the test environment and RPs

4.2 Evaluation environment

This research is implemented and evaluated at the Computer Engineering faculty of Iran University of Science and Technology. The test environment consists of three floors, while the 1st and 2nd floor are overseers to the open space of the ground floor as seen in part (b) of **Fig. 6**. In part (c) of the same figure, the map of the test environment is shown. The floors are ordered on the map such that there is a reasonable distance among floors and due to the effort of current research about the reduction in inter-floor errors, it will be a considerable penalty if an error happens between floors. The dots marked on the map are 80 RPs in which RSSs are recorded in the offline phase.

The system implemented using the APs which were been used normally in the faculty that consisted of 39 APs in the whole building.

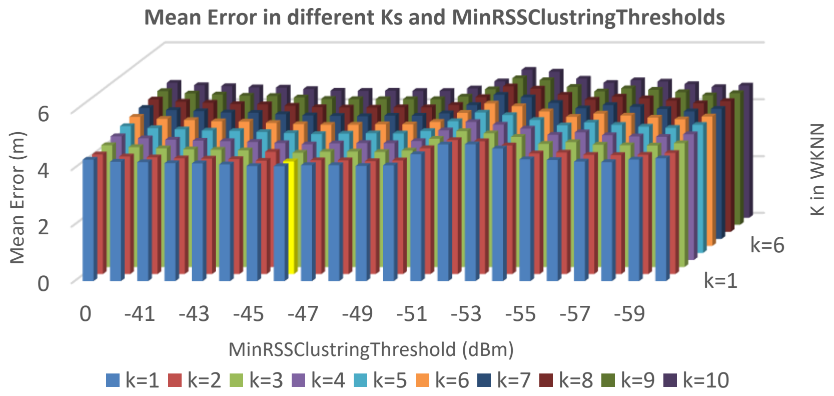


Fig. 7. Comparison of different Ks and *MinRSSClustringThreshold*s by cross-validation

4.3 Evaluation Results

In this section, firstly, the evaluation results of each sub-scheme are presented. After that, the results are compared to a state-of-the-art method proposed in [34].

Evaluation of Min RSS Clustering. To examine the possible effect of the K parameter on the results of the sub-scheme, different values are checked for that via cross-validation. the result of cross-validation for the test environment is shown in **Fig. 7**. As seen, the value of K in KNN doesn't affect *MinRSSClustringThreshold*. The best threshold value is -46dBm for this test environment.

After the determination of the threshold, the algorithm is tested by field tests. The algorithm improved the mean accuracy of about 6% and 95 percentile about 20%. It also lowered the computational time about 1.5 times.

Evaluation of Dynamic grouping based on the last location. As this method works based on physical Euclidean distance, it could be tested only on one floor, because choosing a value for the distance of two floors in a meaningful way wasn't possible.

For determination of the best *MaxMovementThreshold*, a walking track has been done and after that, different thresholds are tested for this track. The best threshold is the one that presents the best accuracy and so least error, which in this case was about 7 meters. Different threshold values and corresponding errors are shown in **Fig. 8**.

After the determination of the threshold, several tests have been done using the algorithm and the result was an average improvement of 47% in mean error and 114% in 95 percentile. Also, it made the computations 10 times faster.

Evaluation of Graph-based Map-Constrained Grouping. Deficiencies of the two former sub-schemes including ignorance of topological constraints lead to this sub-

scheme. In this sub-scheme, it is needed to determine the graph factors which will be multiplied to the weight of RPs with specific hops. The best values for this vector aren't unique, but its values are decreasing in all the best vectors. It's a good practice to have the last factor of the vector equal to zero. This way, RPs further than that factor (distance in hops) are filtered and this is computationally beneficial. A sample of the graph factors vector is shown in **Fig. 9**. Also, the best values for graph factors vector are shown in the chart of **Fig. 10**.
This algorithm improved accuracy about 67% in mean error and 166% in 95 percentile. It has reduced the execution time for about 4.86 times too.

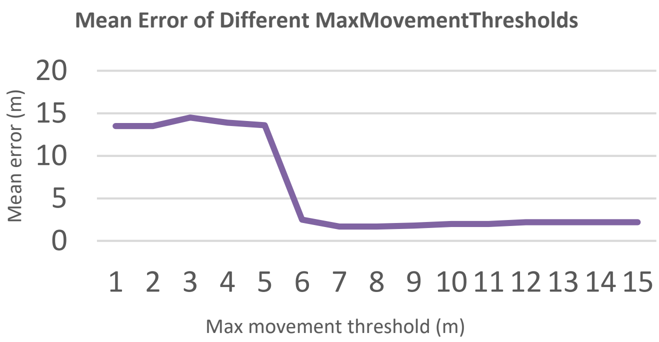


Fig. 8. Mean Error of Different *MaxMovementThresholds*

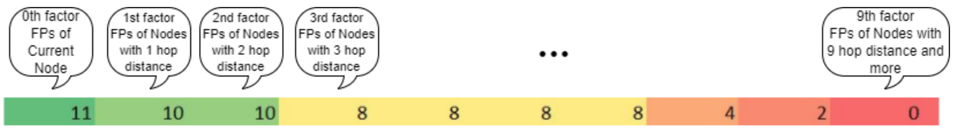


Fig. 9. A sample of graph factors vector

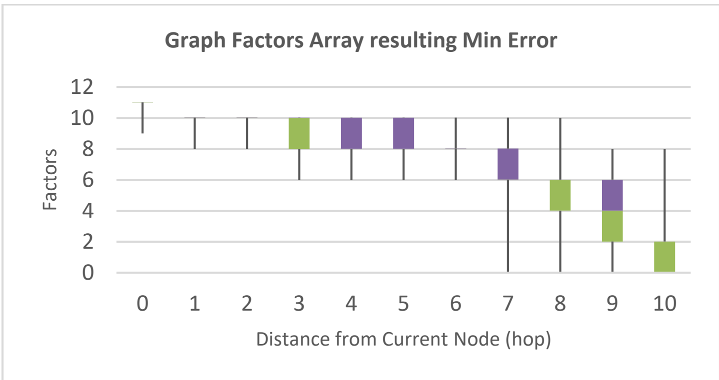


Fig. 10. Box Chart of Graph Factors Array resulting in the Min Error

Comparison to Route Probability Factor (RPF) method from [33]. To compare the proposed method with the most similar and newest related work, the method presented in [34] is implemented and tested. The comparison results show that the proposed method outperforms [34] in terms of accuracy. The reason for this poor performance is that the RPF method isn't suitable for multi-floor positioning. The mean error got by the RPF method is about 6.68m and 95 Percentile is 33m. The calculated Route Probability Factor for different points of the map is presented in **Fig. 11**.

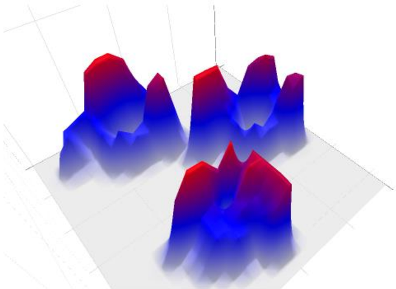


Fig. 11. Route Probability Factor on Test Environment based on the algorithm presented in [34]

Summary of the Results. A summary of the results is given in **Table 2** with and without the presence of each sub-scheme are presented with a 95% confidence interval.

Table 2. Summary of the result of the test of each sub-scheme

	Error Result						Speed Gain
	Mean Error (m)			95th percentile Error (m)			The ratio of execution-time of pure KNN to the proposed method
	Without using sub-scheme	With using sub-scheme	DIFFERENCE	Without using sub-scheme	With using sub-scheme	DIFFERENCE	
Min RSS Clustering	[5.70,6.66]	[5.11, 6.62]	-0.3	[23.95, 38.21]	[17.44, 34.29]	-5.2	1.5
Dynamic Grouping Based on Last Location	[2.94,3.26]	[1.88, 2.39]	-1.0	[7.83,28.63]	[4.61,12.39]	-9.7	10
Graph-Based Map-Constrained Grouping	[5.21,6.79]	[3.06, 4.09]	-2.42	[17.35, 35.88]	[8.63,11.32]	-16.64	4.86

5 Conclusion and Future Work

Wi-Fi fingerprinting IPSs have become widely used, however signal fluctuations reduce their accuracy and efficiency. In this paper, a new method was proposed to overcome the challenges of IPSs, especially in multi-floor buildings which have been less investigated in the past works. Grouping of fingerprints was the main idea of this paper. Different parameters can be used to group fingerprints. In this work, It was performed based on APs received signal strength, the last estimated location of the user, and the map-constrained graph which is matched to the environment map. This idea leads to a reduction in computational cost, increasing the accuracy of the system and is suitable for multi-floor buildings. The result of practical tests approved these claims.

Using proposed methods for other technologies such as BLE, using dynamic graph factors based on simple activity recognition, and testing different graph traversal algorithms and node transition rules are three promising directions for future works.

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