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Smartphone based Improved Floor Determination Technique for Multi-Floor Buildings

Sushil Tiwari and Vinod Kumar Jain

Abstract—**In recent years, most of the existing Indoor Localization Systems (ILSs) mainly used the Wi-Fi based fingerprinting approach to determine the floor position in multi-floor buildings. However, this method suffers from large fluctuation on the Wi-Fi signals which reduces the accuracy of floor estimation. Besides, it is also computationally extensive due to its heavy database size. For resolving these issues, we propose an improved floor determination technique using the atmospheric pressure sensor built in a smartphone. In this paper, the statistical features are extracted from the atmospheric pressure data, then the Fuzzy C-Mean (FCM) clustering algorithm is applied on them to improve the floor determination technique. The proposed work has been evaluated on the "Indoor Positioning Indoor Navigation" (IPIN) 2016 competition dataset. Experimental results are compared with three other well known methods and the participants of IPIN 2016. The proposed method exhibited better results for floor estimation with the accuracy of 98.68%, and the time complexity of proposed method also improved to $O(1)$.**

Index Terms—**Location tracking, Received Signal Strength (RSS), Radio map, Wi-Fi, Mobile device.**

I. Introduction

Nowadays, the demand for an accurate floor determination is rapidly increasing due to the requirement of various location based services. For examples, monitoring the psychiatric patients in a multi-floor hospital, locating the mobile users in a shopping mall, and assisting the firefighters in search and rescue operations inside a skyscrapers building, etc. For these services, the task of determining a mobile user on the correct floor in the multi-storey building is also essential. Till date, various smartphone based floor estimation techniques are developed using Wi-Fi fingerprinting approach [1, 2, 3]. The Wi-Fi fingerprinting mainly works in two phases as (i) Off-line phase, and (ii) On-line phase. In the off-line phase, it measures the Wi-Fi signals from various access points installed in the building to create the Wi-Fi fingerprinting database. This database consists the information including the MAC identification of the access points along with their captured Wi-Fi signals and the ground truths (i.e., building-id, floor-id, and 2D geographical coordinates). In the On-line phase, the captured Wi-Fi signals at the smartphone are matched with the fingerprinting database. Then, the Euclidean distance is used to find the nearest match from the database, and the ground truth is estimated. In one of the research, the authors Alsehly et al. [4] considered the distribution of Wi-Fi signals on each floor to determine the floor position. It takes into account the statistical model that consists of three parameters which are the variance, the range, and the availability. The values of these three parameters present distribution pattern of Wi-Fi signals for each floor. This work is tested in three-storey building and achieved the accuracy of 75%. In another work [5], the researchers have proposed a floor estimation algorithm which computes the sum of visible Wi-Fi signals (i.e. Received Signal Strength (RSS)) corresponding to each floor. Then, each floor is assigned an estimated sum of RSS values. In on-line phase, the sum of RSS values of queried sample is also calculated, and the differences from the values assigned to each floor are estimated. The floor which provides minimum distance from the queried sample is identified as the floor location of the mobile user. But, this work has been tested in the small building and number of installed access points are also less (only 4 APs). Rahman et al. [6] proposed the floor determination technique based on a reduced database for locating the mobile users in multi-floor buildings. The experiment showed that they achieved the floor positioning accuracy of 86% by exploiting only 14% of original fingerprinting database. Thus, the authors of this work claimed to reduce the computation required to estimate the floor position. In the recent work [7], the UMINHO team of IPIN 2016 competition achieved the highest floor estimation accuracy of 95.82% by utilizing the atmospheric pressure sensor's data. They applied a threshold to detect changes between the floors of a particular building. But, it may not be a generalized solution as different buildings have distinguished hight of floors. In this paper, we also utilize the atmospheric pressure data to estimate the floor position in multi-floor buildings. For making a significant improvement over the work done by UMINHO team, we extract the various statistical features from the atmospheric pressure data, then apply the Fuzzy C-Mean (FCM) clustering algorithm on them. The performance of our proposed work is evaluated on IPIN 2016 dataset. It is also compared with three benchmark methods and the solutions provided by the participants of IPIN 2016 competition.

The remaining part of this paper is structured as follows. Section II provides the detailed description of IPIN 2016 competition dataset. The proposed scheme for floor estimation is presented in section III. Experimental results and the comparison with existing methods are provided in section IV. Finally, section V summarizes the paper.

II. Description of IPIN 2016 Competition Dataset

In our work, we have utilized the dataset as provided for IPIN 2016 competition [8]. The organizers of this competition have collected the data from four different buildings in which three of them are multi-floor buildings as shown in Fig. 1. This dataset contains the measurements of various inbuilt sensors of a smartphone, i.e., Wi-Fi, Magnetometer, Accelerometer, Barometer, Gyroscope, etc, with timestamps.

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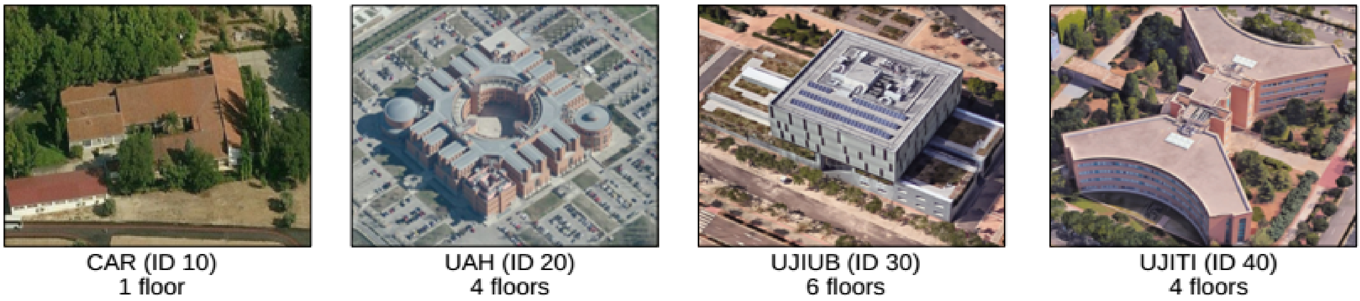

Figure 1: Satellite view of the buildings used in the construction of IPIN 2016 dataset [8]

Table I: Details of the training log files

Logfiles #	Building-ID	Number of floors	Number of landmark	Smartphone
(1,2,3,4)	CAR-10	(1,1,1,1)	(75,75,52,52)	(S3,S3mini,S3,S4)
(5,6,7,8,9,10)	UAH-20	(3,3,4,4,2,2)	(67,67,64,64,29,29)	(S3,S4,S3,S4,S3,S4)
(11,12,13,14,15)	UJIUB-30	(6,6,6,6,6)	(58,58,59,59,60)	(S3,S3,S3,S3,S3)
(16,17)	UJITI-40	(3,3)	(360,291)	(GN5,GN5)

Table II: Details of the testing log files

Logfiles #	Building-ID	Number of floors	Number of landmark	Smartphone
(6,9)	CAR-10	(1,1)	(76,76)	(S3,S4)
(3,5,7,8)	UAH-20	(4,3,4,3)	(65,42,65,42)	(S3,S4,S4,S3)
(2)	UJIUB-30	(6)	(91)	(S3)
(1,4)	UJITI-40	(3,3)	(360,291)	(HW,SP)

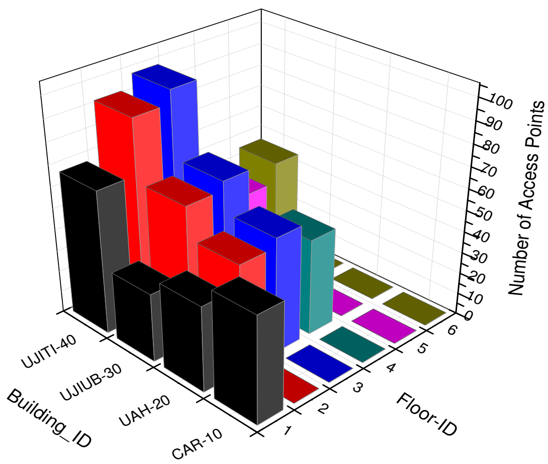

Figure 2: Number of visible APs at different buildings

The dataset also includes some tuples which contain the ground truth for particular timestamps. As different sensors have distinguished rate of sampling. Therefore, all the samples are collected with their timestamps so that the samples obtained from different sensors can be synchronized with each other. In IPIN 2016 competition, most of the participants used Wi-Fi fingerprinting technique which needs a Wi-Fi fingerprint database. But, in the dataset, those samples which included ground truth were not collected at exactly same time instants when the Wi-Fi fingerprints are collected. This makes it difficult to build a good quality of Wi-Fi fingerprinting database. As each Wi-Fi sample is not associated with a clear ground truth sample. Therefore, a mechanism is required to determine the ground truth of each Wi-Fi sample. It also applies to the samples collected from other sensors. In this dataset, a total of 2971 Wi-Fi fingerprints are built by associating each Wi-Fi fingerprint with nearest (in term of timestamps) ground truth. The IPIN dataset contains a total of 816 access points (APs), and the distribution of these APs among four buildings is shown in Fig. 2. The dataset consists 26 log files in which 17 log files are used for training and 9 log files for evaluating the work as presented in Table I and Table II respectively. For better understanding the representation of the dataset in these tables, we take an example. Suppose, we consider the fourth tuple i.e., (16, 17) in Table I, Here, the first column contains the sequence number of the log files i.e., 16 and 17. The second column represents the building-id where the data of these log files (i.e.,16 and 17) are collected. Similarly, third and fourth columns represent the number of floors and landmarks involved in collecting the data of these log files. At last, the fifth column consists the smartphone utilized to capture the data of particular log files. The list of smartphones used in the data collection process of IPIN 2016 dataset is presented in Table III.

III. Proposed Scheme

As IPIN 2016 dataset is collected from four different buildings, therefore we first need to identify the particular building, then we determine the floor position of mobile user in that building. Thus, the proposed scheme is mainly divided into two subparts as (i) building identification, and

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Table III: List of smartphone involved in construction of IPIN 2016 dataset

Smartphone	Description
S3	Samsung Galaxy S3
S3mini	Samsung Galaxy S3 mini
S4	Samsung Galaxy S4
GN5	Google Nexus 5, LG Electronics,
HW	Huawei G630, Huawei
SP	Sony Xperia SP, Sony

(ii) floor identification. For the building identification, we utilize Wi-Fi majority rule [9] as described in subsection III-A. For the floor determination, we propose an improved floor determination technique by applying Fuzzy C-Mean clustering algorithm on the atmospheric pressure data as described in subsection III-B in detailed.

A. *Wi-Fi majority rule*

Firstly, we apply Wi-Fi majority rule [9] to identify the particular building. In this approach, the Wi-Fi fingerprinting database is divided into fixed number of subsets depending on the number of involved APs. For example, there are 816 APs are used to construct IPIN dataset. Then, the same number of subsets are created from the original dataset, in which each tuple within a subset consists the strongest signal corresponding to particular AP. In order to identify the correct building, the AP having strongest signal among other visible APs is identified in the quired sample. Then, we apply a majority rule in the same subset where identified AP has the strongest signal. This approach is very efficient in the terms of computational effort as it does not require to compute the similarities between Wi-Fi fingerprints. It also verified to be very reliable with accuracy of 100% for determining the correct building as tested using IPIN 2016 dataset by [7]. The complete steps of identifying the correct building are described in Algorithm 1. After recognizing the building, we utilize the atmospheric pressure data to determine floor position of the mobile user as explained in subsection III-B.

Algorithm 1 Wi-Fi majority rule algorithm for building identification

Input: Wi-Fi fingerprints
Output: Building-ID

1: Select AP_{h1}, the strongest AP observed in queried Wi-Fi fingerprints FP_q.
2: Develop a reduced database F', from the original Wi-Fi fingerprint database F where AP_{h1} must be the strongest AP.
3: Repeat the steps 1 and 2 using next strongest AP (i.e.,AP_{h2}, AP_{h3}, ..., till the last AP in FP_q.) If F' is empty.
4: Calculate the number of Wi-Fi fingerprint tuples in reduced database F' corresponding to each building, then find the most frequent building (majority rule).

B. *An Improved Floor determination Technique*

In this work, we utilize the information received from atmospheric pressure sensor. The atmospheric pressure continuously degrades when user moves to upper floor as noticed from the data plotted in Fig. 3.

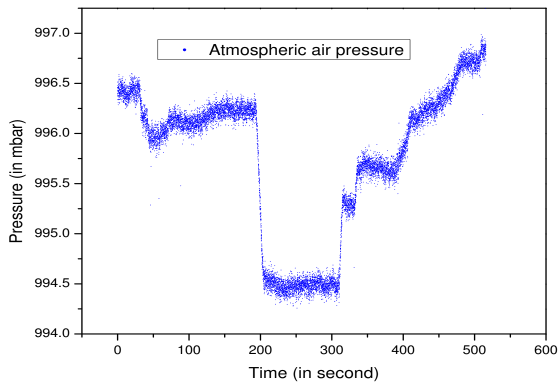

Figure 3: Measurements of pressure sensor data

It infers that relative variation in atmospheric pressure has a strong correlation with changes in floor. Therefore, floor position may be determined by setting a threshold for each floor, but it can not be a generalized solution because different buildings have distinguished hight of floors. To resolve this issue, we first extract the statistical features from the atmospheric pressure data as listed in Table IV.

Table IV: Statistical Features

RMS	$\sqrt{\frac{1}{S}\sum_{i=1}^{S} P_i^2}$
Kurtosis	$\frac{1}{S}\sum_{i=1}^{S}\frac{(P_i-\bar{P})^4}{\sigma^4}$
Skewness	$\frac{1}{S}\sum_{i=1}^{S}\frac{(P_i-\bar{P})^3}{\sigma^3}$
Peak to Peak	$P_{max} - P_{min}$
Crest Factor	$\frac{\max(P_i)}{RMS}$
Shape Factor	$\frac{RMS}{\frac{1}{S}\sum_{i=1}^{S} P_i}$
Margin Factor	$\frac{\max(P_i)}{\frac{1}{S}\sum_{i=1}^{S} P_i}$
Impulse Factor	$(\frac{\max(P_i)}{\frac{1}{S}\sum_{i=1}^{S}\sqrt{P_i}})^2$

Here, S represents the number of atmospheric pressure data captured between two consecutive Wi-Fi samples. P_i denotes atmospheric pressure measured at i^{th} timestamps. After computing the statistical features, FCM clustering algorithm is applied on them to cluster the atmospheric pressure data according to the number of floors in the building. The computed centroids of each cluster are utilized to distinguish the floor. For determining the floor position of mobile user, the differences between the quired sample and the centroid of each cluster are computed. Then, the cluster centroid is identified which has the minimum distance from the queried sample. Thus, the floor is identified as each floor is already assigned with cluster centroid. The detailed steps of FCM are described in Algorithm 2.

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Algorithm 2 Fuzzy C-Means (FCM) Clustering algorithm for Floor Determination

Input: 8-dimensional atmospheric pressure data
Output: Floor-ID

1: Let assume that n atmospheric pressure data samples denoted by p_i, where $i = 1$ to n, have to be clustered.
2: Select the number of clusters according to number of floors in the particular building, i.e., n_c, and $1 < n_c \leq n$.
3: Initialize fuzzy membership matrix M having dimension of $n \times n_c$ with random values, where $M_{ij} \in 0$ to 1.0, also $\sum_{j=1}^{n_c} M_{ij} = 1.0$, for each i.
4: Determine the centroid of the cluster δ_j, for j^{th} cluster using Eq. 1.

$$\delta_j = \frac{\sum_{i=0}^{n} M_{ij}^{f} p_i}{\sum_{i=1}^{n} M_{ij}^{f}} \tag{1}$$

5: Estimate the distance between j^{th} cluster centroid and i^{th} atmospheric pressure data sample with respect to each dimension using following Eq. 2.

$$d_{ij} = \parallel (p_i - \delta_j) \parallel \tag{2}$$

6: Modify the matrix M, if only $d_{ij} > 0$, as in Eq. 3.

$$M_{ij} = \frac{1}{\sum_{c=1}^{n_c} (\frac{d_{ij}}{d_{ic}})^{\frac{2}{f-1}}} \tag{3}$$

Here, f represents cluster fuzziness level, and $f > 1$.

7: Repeat from step 4 to 6 till the Matrix M changes such that $M \leq 0.1$, here 0.1 is termination threshold.

IV. Experimental Results and Discussion

In this section, the performance of proposed floor determination technique is evaluated and compared with existing methods. For evaluating this work, we have utilized the IPIN 2016 competition dataset which contained the nine evaluation log files (i.e. T1 to T9). The detailed description of these log files is already provided in section II. In all the 9 trials, the proposed method obtained the highest floor estimation accuracy of 98.68% (average of nine trials) among other existing methods as illustrated in Table V. The proposed method has achieved the accuracy of 100% in five trials out of nine trials. We also analyze the floor estimation error corresponding each multi-floor building individually. Fig. 4 shows floor estimation error for each floor of the UAH-20 building. In this building, proposed method has the floor estimation error of 0.93% (i.e., an average of 4 floors in UAH-20 building), while the best method (i.e., UMINHO team) among other existing methods has the floor estimation error of 1.95% in the same building. Similarly, Fig. 5 and Fig. 6 also clearly indicate that the proposed method has the least floor estimation error corresponding to each floor of UIUBI-30 and UJITI-40 buildings respectively. From the computation effort point of view, we have done a significant improvement over the Wi-Fi fingerprinting based floor estimation. Wi-Fi fingerprinting methods need to compute the similarities between the quired sample and each Wi-Fi fingerprints of the database. Therefore, it takes $O(n)$ time to determine the floor, where n represents the number of Wi-Fi fingerprints in the database. While the proposed method requires to compute the similarities from the centroid of each cluster which are very less in comparison size of Wi-Fi fingerprinting database. The number of clusters depends on the number of floor in the particular building. As $n >> f$, so the time complexity of proposed method is also improved to $O(1)$ from $O(n)$.

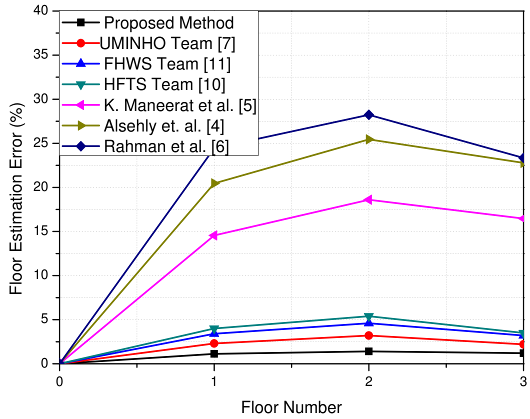

Figure 4: Floor estimation error for building UAH-20

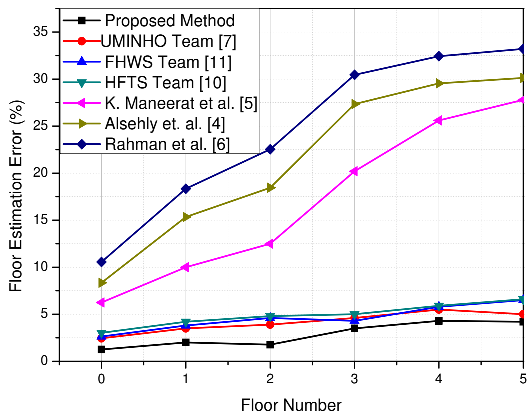

Figure 5: Floor estimation error for building UJIUB-30

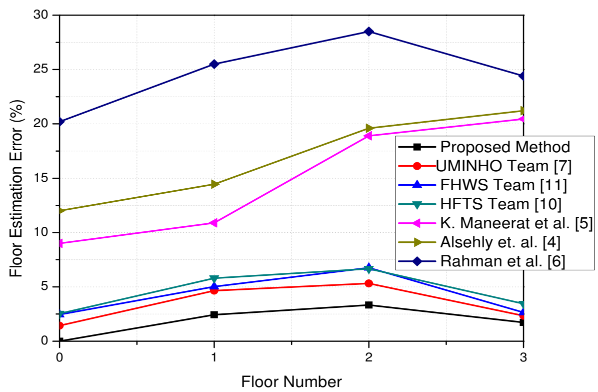

Figure 6: Floor estimation error for building UJITI-40

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Table V: Percentage of floor accuracy corresponding to different floor estimation techniques

	Percentage of floor accuracy									
Techniques	T1	T2	T3	T4	T5	T6	T7	T8	T9	Total accuracy
Alsehly et al. [4]	62.64%	74.15%	68.73%	77.17%	66.39%	100%	71.06%	70.61%	100%	76.75%
K. Maneerat et al. [5]	71.05%	72.57%	63.35%	74.24%	69.49%	100%	73.76%	81.34%	100%	78.42%
Rahman et al. [6]	66.12%	44.41%	31.74%	57.33%	37.61%	100%	40.91%	38.53%	100%	57.41%
HFTS Team [10]	97.28%	89.01%	84.62%	97.12%	93.62%	100%	100%	88.10%	100%	94.41%
UMINHO Team [7]	97.84%	80.22%	96.45%	93.75%	94.15%	100%	100%	100%	100%	95.82%
FHWS Team [11]	93.48%	78.02%	96.09%	94.87%	95.02%	100%	100%	100%	100%	95.27%
Proposed Method	98.21%	97.10%	97.39%	100%	95.5%	100%	100%	100%	100%	98.68%

V. Conclusion

This paper presented the smartphone based improved floor determination technique for multi-floor buildings. The proposed method achieved the floor estimation accuracy of 98.21%. It infers significant improvement over the existing technique which performs best among other five floor estimation methods. Besides, the time complexity of proposed method is improved to $O(1)$. Thus, the presented work not only improves the accuracy of floor estimation but also decreases the computation time. This research can be utilized to extend the capability of indoor localization for multi-floor buildings.

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