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A MULTI-FLOOR INDOOR POSITIONING METHOD BASED ON WI-FI AND BAROMETER FUSION

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Abstract. *The multi-floor positioning accuracy has a great impact on indoor positioning accuracy. To improve multi-floor positioning accuracy, we consider both the air pressure and Wi-Fi signals, and propose a multi-floor indoor positioning method. We exploit the relationship of air pressure hierarchically and carry out our approach through two phases, i.e., an offline phase for clustering the Wi-Fi fingerprints of the same floor and an online phase for continuous positioning. In the offline phase, we use air pressure to estimate the average floor spacing and construct the Wi-Fi fingerprint database of each floor. In the online phase, we estimate the user's initial floor and altitude to locate the user continuously. Furthermore, the Wi-Fi signals are smoothed and filtered to further improve the positioning accuracy in this paper. Extensive real experiments have been conducted in a research lab. The experimental results show that the proposed approach can improve the positioning accuracy to 93.31%, and achieve 100% accuracy in a short time.*
Keywords: Indoor positioning, Multi-floor, Wi-Fi, Barometer, Clustering, Data filtering

1. **Introduction.** With the popularization and development of smartphones, there are more and more scenes including fire rescue and warehouse positioning where users need indoor positioning. User-based positioning services have become a hot issue in the community [1,2]. As an important part, floor positioning has attracted the attention of researchers.

In the field of indoor positioning, methods based on Wi-Fi have become a research hotspot [3]. The methods are mainly carried out by Wi-Fi ranging or building a Wi-Fi fingerprint database. Since Wi-Fi received signal strength (RSS) is easily disturbed by the environment, the ranging-based method cannot obtain accurate results. In contrast, the fingerprint-based method is less affected. By default, RSS refers to Wi-Fi RSS.

Since the air pressure values (APVs) decrease with increasing altitude, researchers can estimate a current floor (CURF) by the altitude difference between a CURF and a reference floor (RF) [4]. However, researchers require to know the height of floors in advance. By contrast, our method can avoid this problem. In the following, altitude and height are called altitude uniformly.

There are three contributions as follows. Firstly, a Wi-Fi fingerprint database is generated by hierarchical clustering according to the APVs, which avoids recording the floors

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of access points (APs) and reference points (RPs). Secondly, the average altitude of the floors is estimated according to the APVs, which avoids measuring the floor altitude and updating the APV of RF regularly. Finally, a positioning method based on Wi-Fi and barometer fusion is proposed, which can improve the positioning accuracy to 93.31%, and achieve 100% accuracy in a short time.

2. **Related Work.**

For the floor discrimination method based on Wi-Fi ranging, the distance between the point to be measured (MP) and the AP through the signal attenuation model (SAM) is calculated first, and then the floor information of the MP is estimated.

Liu and Yang [5] located the floor, where the AP is closest to the user, as the positioning floor. However, the APs' positions need to be known, which are difficult to be measured in reality. The indoor environment is complex and changeable, so it is difficult to find an SAM to map the relationship between Wi-Fi RSS and distance accurately. The industry has proposed two solutions to solve this problem. One is the method based on deep learning. Pichaimani and Manjula [6] proposed a recognition method, combining principal feature augmented sampling with Kohonen deep structure, which provides high indoor positioning accuracy with less time. Due to the characteristics of deep learning, a large amount of data needs to be collected to train a model.

The other is the fingerprint-based method. There is no need to know the floors of the APs in this method. A fingerprint attention mechanism for floor discrimination was proposed by Zhang et al. [7]. In the offline phase of a fingerprint-based method, a lot of manpower and time are needed to create a fingerprint database. Thus, Caso et al. [8] introduced an indoor positioning system. It relied on RSS prediction based on a multi-wall and multi-layer propagation model to generate discrete RSS maps. This method reduced the number of fingerprints collected, and the time consumption of manual data collection.

Barometers are used for positioning by some scholars. Li et al. [9] discussed the necessity of applying a barometer to floor positioning. Jeon et al. [10] used the relationship between an APV and altitude to calculate the floor. Strozzi et al. [11] judged the number of changed floors by setting a threshold and comparing it with the altitude of an initial floor (INITF). Because APVs are affected by temperature, APVs of RFs need to be calibrated frequently, which makes positioning work complex. Meanwhile, the accuracy of a single-sensor-based positioning method is low, so we use a multi-sensor fusion method to improve the positioning accuracy.

Shen et al. [12] proposed a system named BarFi, which first combined Wi-Fi and a barometer. It included a hierarchical clustering method based on APVs and a K-means clustering method based on RSS. This method needs to measure the distance between floors in advance. Huang et al. [13] proposed using hidden Markov to correct accidental floor positioning errors. Cock et al. [14] fused Wi-Fi, accelerometers, and barometers to locate floors. They used the Viterbi algorithm to fuse motion states and RSS for floor recognition. They used more sensors to complete the floor positioning, but ours only requires Wi-Fi and a barometer to complete the task. To predict the floor, Lin and Shin [15] used a deep learning model to calculate pressure sequences. Compared with the above, our method does not need to know the altitude of floors in advance and avoids the need to update the APVs of RFs frequently. Our method effectively improves positioning accuracy.

3. **Multi-Floor Indoor Positioning Method Based on Wi-Fi and Barometer Fusion.**

3.1. **Overview.**

Our positioning method is divided into offline and online phases. The framework of the positioning method is shown in Figure 1.

In the offline phase, RPs are divided on each floor. RSS and APVs are collected at each RP in turn by using intelligent devices. First, the RSS values are clustered using

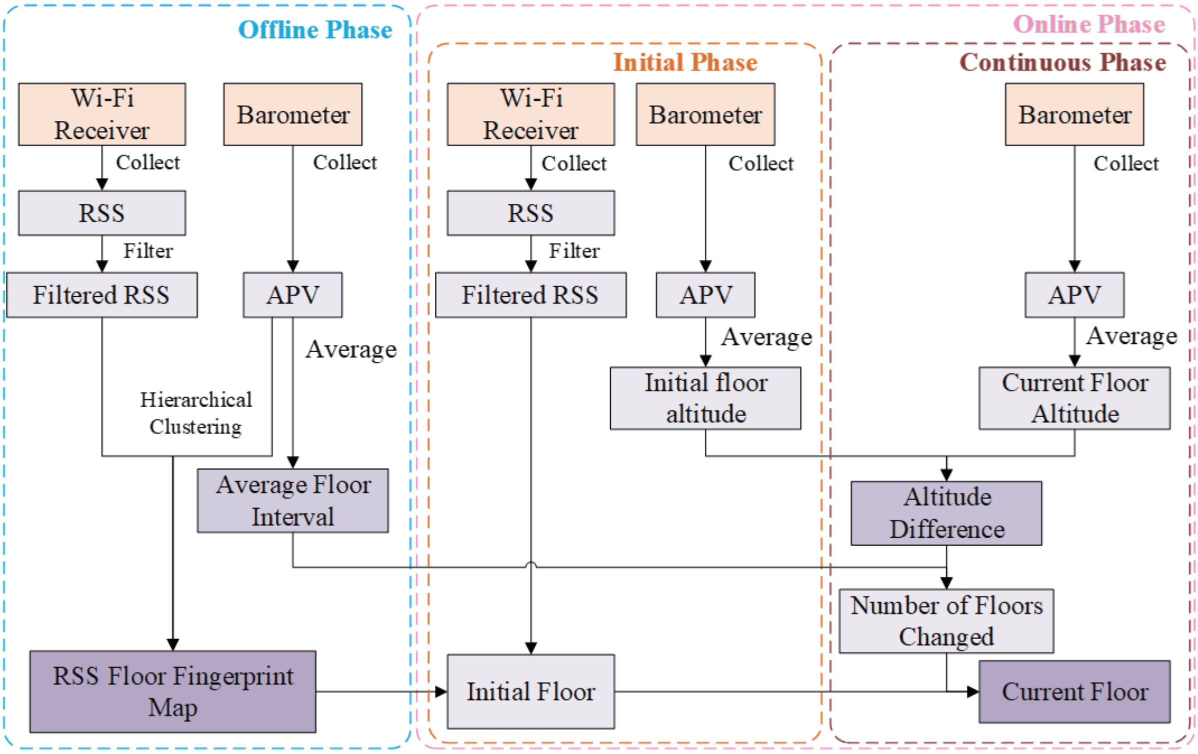


FIGURE 1. Framework of the multi-floor positioning method

the Agnes clustering algorithm, and then smoothed to eliminate the interference of noise. Finally, the average floor altitude is estimated with the APVs.

The online phase is divided into an initial positioning phase and a continuous positioning phase. In the initial phase, a user's RSS and APVs are collected. First, the RSS is smoothed and filtered, and then the distances between the RSS and each fingerprint are calculated. We select the k nearest fingerprints and take the floor with the largest number of fingerprints as the INITF. Then, the altitude of the INITF is calculated by using the APVs. In the continuous phase, a user's APVs are collected. First, the altitude of the CURF is calculated by APVs, and then the number of floors is obtained by using the altitude difference between the CURF and the INITF. Finally, the CURF is obtained.

3.2. Basic positioning model.

3.2.1. *Positioning model based on Wi-Fi fingerprint.* In the offline phase, the RSS of each AP is collected at each RP. Assuming that there are n APs, the fingerprint of the i-th RP is recorded as FP_i, that is,

$$FP_i = ((x_i, y_i), (MAC_m, RSS_i(m))), \quad m \in (1, 2, \ldots, n) \tag{1}$$

where (x_i, y_i) is the position of the i-th RP, and $(MAC_m, RSS_i(m))$ is the MAC address and RSS of the m-th AP. Finally, the fingerprints of all RPs are stored to create a Wi-Fi fingerprint database.

In the online phase, assuming that the signals of P APs are detected at the MP. The Euclidean distance $dist_i$ from the RSS vector $s = (RSS_1, RSS_2, \ldots, RSS_P)$ of the MP to the i-th fingerprint FP_i is calculated, i.e.,

$$dist_i = \sqrt{\sum_{j=1}^{P} (RSS_j - RSS_i(j))^2} \tag{2}$$

The smaller the distance is, the closer s and the fingerprint are. Different from the method in [4], we take the floors $FPSet$ of the k nearest fingerprints to calculate the floor

iF of the MP. Thus, a mode function $Mo(\cdot)$ is used, i.e.,

$$iF = Mo(FPSet) \tag{3}$$

3.2.2. *Positioning method based on air pressure.* The relationship between an APV P and altitude A can be concluded as follows:

$$A = 44330 \times \left(1 - \left(\frac{P}{P_0}\right)^{\frac{1}{5.255}}\right) \tag{4}$$

where P_0 is the mean sea level pressure, which is 1013.25 hPa. For the altitude a and a_r of two different floors, the altitude difference Δa is

$$\Delta a = a_r - a \tag{5}$$

where a_r and a are the altitudes of an INITF and a CURF calculated according to Formula (4). To get the number of changed floors, we compare the altitude difference Δa with the floor altitude. As shown in Figure 2, instead of measuring the floor altitude manually, we use the average floor altitude which is estimated by using the APVs collected in the offline phase.

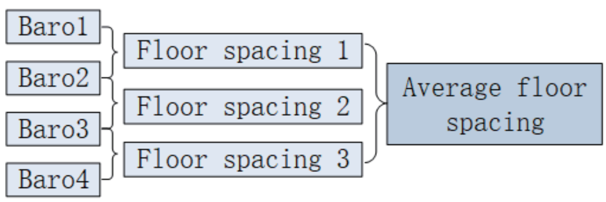


FIGURE 2. Estimated average floor spacing

Assuming that the positioning area is a building with four floors, we average the APVs collected on each floor to obtain $baro1$, $baro2$, $baro3$, and $baro4$ in Figure 2. The values are sorted from large to small, that is, $baro1 > baro2 > baro3 > baro4$. The two similar APVs represent the APVs of adjacent floors. According to Formula (4), we calculate the altitude difference between two adjacent floors, i.e., the floor spacing. We take the average of all floor spacings as the average floor spacing $averA$ of the building, that is,

$$averA = \frac{\sum_{i=1}^{k} a_i}{k} \tag{6}$$

where k is the number of floors, and a_i refers to the floor spacing of the i-th floor. According to the threshold comparison method, we use the altitude difference between a CURF and an INITF to estimate the changed floors. The threshold μ is set to half the average floor spacing, i.e., $\mu = \frac{averA}{2}$. First, we judge the number of changed floors CF. The difference between $|\Delta a|$ and the altitude of CF floors should not exceed μ, i.e., $cF = \left\lceil \frac{|\Delta a| - \mu}{averA} \right\rceil$. Then we judge the direction of change. If $\Delta a < 0$, it means that the user moves down, and $cF = -cF$ at this time. Finally, the number of CURF f is obtained, that is,

$$f = iF + cF \tag{7}$$

3.3. **Data filtering rules.** Wi-Fi signals are easily disturbed by surroundings. To improve the quality of the Wi-Fi fingerprint database, we propose a data filtering rule. First, RSS is collected at each RP many times. Then the RSS is processed by a smoothing filter to obtain the characteristic data of the corresponding RP.

When we collect data, sometimes we cannot detect the signals of an AP, i.e., missed detection. If there are many signals missed detection at an RP, it is considered that the signals of the AP at this RP are weak and the AP is meaningless to this RP.

Based on the above analysis, we assume that n APs are detected during data collection, and data is collected m times at each RP. The RSS vector of the i-th AP collected at an RP is $R_i = (RSS_1(i), RSS_2(i), \ldots, RSS_m(i))$. The signal values of missed detection are set to 0, and then the data is filtered as follows.

Take the i-th AP as an example. The number of 0 in R_i is counted and marked as num. If num exceeds half of the detection times $0.5m$, the characteristic r_i of the AP at this RP is set to 0, i.e., $r_i = 0$. If $num \leq 0.5m$, remove all values of 0 from R_i. Then, two maximum and two minimum values are removed, which can prevent data retention when users move up and down. Finally, the remaining RSS is averaged as the feature of the AP, that is,

$$r_i = \frac{\sum_{j=1}^{m-num-4} RSS_j(i)}{m - num - 4} \tag{8}$$

3.4. **Clustering Wi-Fi data with a barometer.** During data collection, we found that the fluctuation in the pressure of the same floor is about 0.01-0.05 hPa. It is far less than 0.38-0.42 hPa, which is the pressure difference between adjacent floors. Compared with RSS, the air pressure is more stable and has obvious differentiation. Thus, we cluster all the APVs and gather the RPs of the same floor into the same cluster. From this, we can know which floor the RSS belongs to.

Here we choose a hierarchical clustering algorithm. AGNES is a hierarchical clustering algorithm with a bottom-up aggregation strategy. The execution process of the algorithm is divided into four steps. Step 1: Begin by calculating the distance matrix between all pairs of data points in the dataset. Step 2: Initialize each data point as its own cluster. Step 3: Find the closest two clusters based on the distance matrix, and merge them together. Step 4: Update the distance matrix to reflect the newly merged cluster. Then, repeat Step 3 and Step 4 until the distance between the nearest 2 clusters is greater than the threshold.

4. Experimental Results and Analysis.

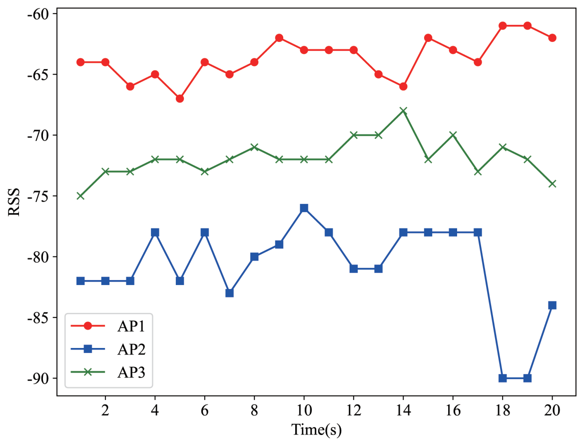
4.1. **Experimental environment and data acquisition.** We made a detailed performance evaluation of our positioning method in the School of Information Science and Engineering of Yanshan University which has 6 floors. Multiple RPs were randomly set near the stairs of each floor. We collected RSS by a vivo X6, and APV by an iPad pro. We collected data 20 times at each RP. After collection, 1200 pieces of data were used for training and 600 pieces for testing. To measure the positioning accuracy, assuming there are n pieces of data tested, in which m pieces are correctly positioned ($m \leq n$). Then the accuracy rate Acc is

$$Acc = \frac{m}{n} \times 100 \tag{9}$$

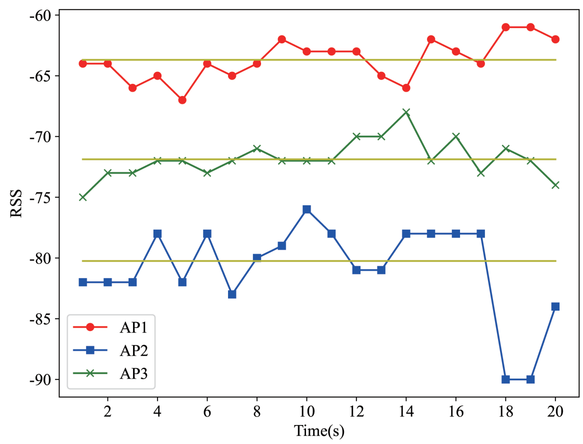
Generally, a cumulative error is used to represent a positioning effect. We assume that the number of the MPs where the floor positioning error is within the range of i floors is k ($k \leq n$). Then the probability $p(i)$ of the cumulative error reaching i floors is that

$$p(i) = \frac{k}{n} \tag{10}$$

4.2. **The effect of data filtering on positioning.** To verify that the data filtering can effectively improve the positioning accuracy, the RSS of three APs collected at the same RP were used in the experiment. The RSS before and after filtering is shown in Figure 3. The initial positioning accuracy is shown in Table 1. In Figure 3(a), RSS fluctuates greatly, especially when RSS is weak, such as AP2. It can be known that the original signals are affected by surroundings easily, which makes them unstable. The straight lines in Figure 3(b) are the filtered RSS. As shown in the figures, the filtered data can reflect the signal characteristics of the positions. In Table 1, the positioning accuracy of INITF can reach



(a) Raw data



(b) Filtered data

FIGURE 3. Raw data and filtered data

TABLE 1. Initial floor positioning accuracy of the two experiments

	Before filtering	After filtering
Accuracy (%)	88.3	100

100% when the filtered RSS is used. However, without filtering, the accuracy is only 88.3%. The results show that our filtering rule can improve positioning accuracy.

4.3. **Verification of hierarchical clustering.** According to the fact that the floor spacing of buildings in China is usually $3m$, and the threshold is set to 0.36 [11]. The clustering results are shown in Figure 4, and the number of clusters after clustering is the number of floors. From the figure, we can see that there are 6 floors in the positioning area, which is consistent with the fact. It can be proved that the RPs of the same floor can be divided into the same cluster through hierarchical clustering. Figure 4 also shows that the air pressure fluctuation of the same floor is small, and the difference between different floors is large.

4.4. **The effect of the number of APs on the positioning.** The accuracy of the initial phase plays an important role in our method. To verify its relationship with the

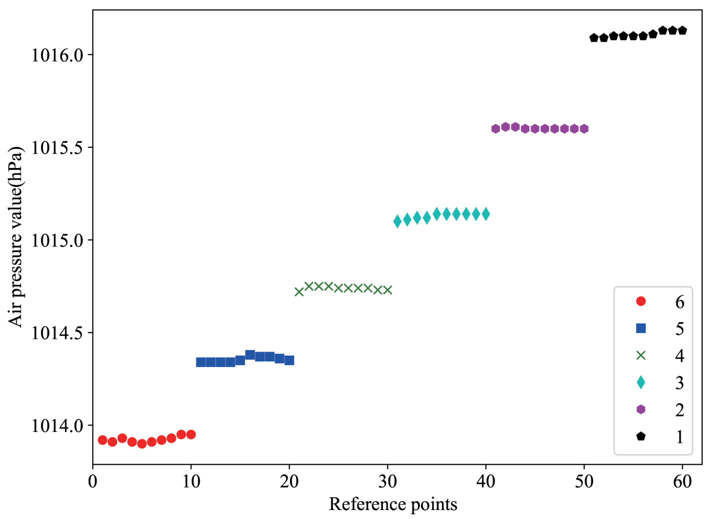


FIGURE 4. Clustering RSS with APVs

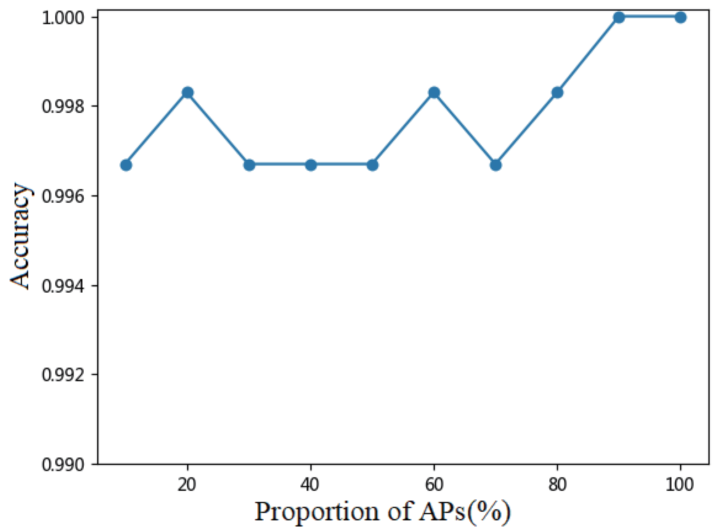


Figure 5. Initial positioning

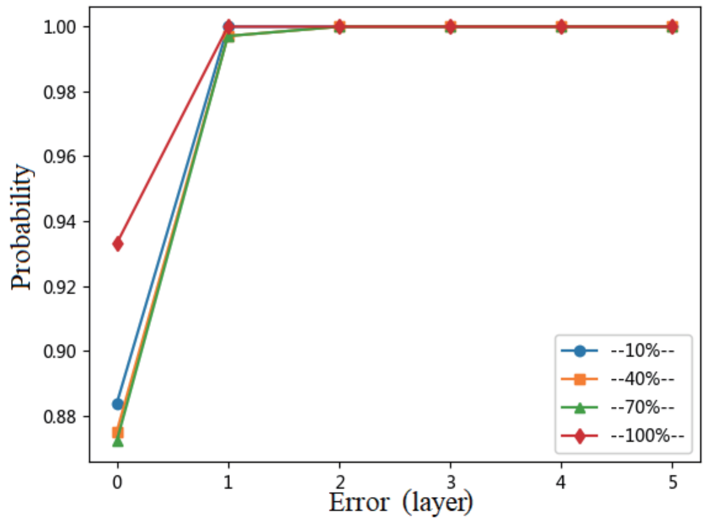


Figure 6. Overall positioning

Table 2. Initial floor positioning accuracy under different AP numbers

Proportion of AP (%)	10	20	30	40	50	60	70	80	90	100
Accuracy (%)	99.67	99.83	99.67	99.67	99.67	99.83	99.67	99.83	100	100

number of APs, we discuss the initial positioning and the overall positioning effects when the number of APs is different. The positioning results are shown in Figure 5 and Figure 6. The accuracy of initial positioning is shown in Table 2. 227 APs are detected in our experiments. As shown in Figure 5 and Table 2, positioning accuracy increases with the increasing number of APs. However, it decreases in some parts. That is because the increased APs are unevenly distributed, which interferes with the positioning. When positions are far away from these APs, positioning errors will increase for the signals are too weak. The table also shows that using 90% of APs can achieve 100% accuracy, so we use more than 90% of APs to locate the INITF. The cumulative error distribution function is shown in Figure 6. Without time limitation, we can achieve the best positioning accuracy of 93.31% by using all APs, which is higher than using part of the APs, and there is a 100% probability of reaching one layer of error.

4.5. **The effect of temporal stability on the positioning.** Over time, the temperature will affect the air pressure. To verify the effect of time change on the positioning method, we discuss the positioning effect in different time ranges. Since we aim at short-time positioning, we analyze the change of positioning results with time in one hour. We conduct experiments every 10 minutes, and the results are shown in Figure 7. Through observation, it is found that 100% positioning accuracy can be achieved within 20 minutes. With the increase of time, the overall positioning accuracy shows a downward trend. At 40 minutes, the positioning accuracy increased slightly, because the temperature at that time was close to the initial temperature. It is found that our method can achieve ideal results in a short time.

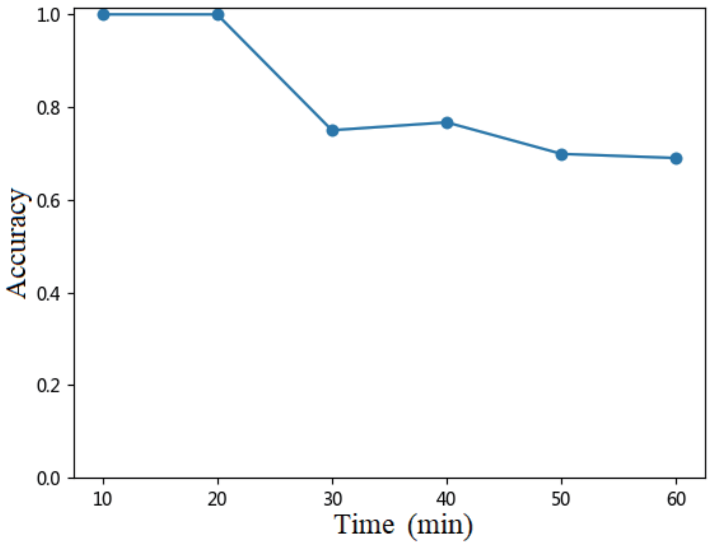


FIGURE 7. Relationship between time and accuracy

4.6. **Comparison with other methods.** In this section, we compare our method with the method using a barometer alone [11]. As shown in Figure 8, both methods have a 100% probability of reaching one level of error. The accuracy of our method is 93.31%, which is higher than the accuracy obtained by the comparative method of 81.98%. Thus, our method can effectively improve positioning accuracy.

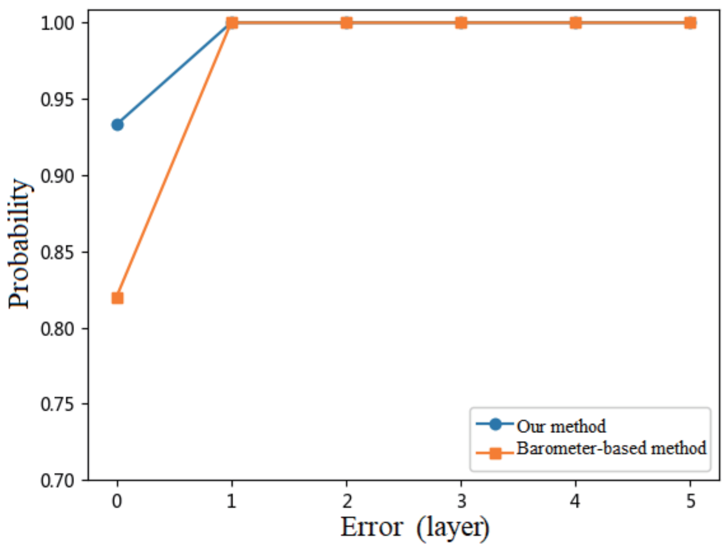


FIGURE 8. Comparison with other methods

5. **Conclusions and the Future Work.** In this paper, we propose a multi-floor positioning method for indoor positioning. The method combines the offline and online phases, in which the offline phase performs Wi-Fi fingerprint clustering and the online phase performs continuous user location. The APVs collected from the built-in barometers of smart devices are used to estimate the average spacing of different floors and improve the clustering accuracy. By smoothing and filtering the Wi-Fi signals, our approach can obtain accurate positioning results. Extensive experiments in a real environment indicate the proposed approach can achieve 100% accuracy in a short time and obtain better positioning accuracy than other barometer-based methods. In our future work, we will pay more attention to using fewer APs to achieve 100% positioning accuracy.

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