



WiFi CSI Fingerprinting Positioning Based on User Rotation

Jiahao Zhang¹, Ming Zhang¹, Zuoliang Yin², Zhian Deng^{1(✉)},
and Weijian Si¹

¹ College of Information and Communications Engineering,
Harbin Engineering University, Harbin 150001, China
dengzhian@hrbeu.edu.cn

² School of Electronics and Information, Qingdao University,
Qingdao 266000, China

Abstract. This paper studies the indoor fingerprinting positioning using Channel State Information (CSI) in commercial WiFi network environment. In this paper, we improve the existing indoor fingerprinting positioning method by considering the influence of human body absorption on CSI signal amplitude and collecting CSI data with user rotation at each reference location. The whole positioning process includes two stage: offline stage and online stage. In the offline stage, we extract features from the filtered CSI data of three APs at each reference location to construct CSI fingerprints. In the online stage, we first compare the feature vectors of filtered CSI data with fingerprints, and then calculate the Euclidean distance between the online CSI feature vector and fingerprints. Finally, user location will be obtained by the K Nearest Neighbor (KNN) algorithm. Experiments proved the performance improvement of the proposed CSI fingerprinting positioning method.

Keywords: Indoor positioning · CSI · Fingerprint · KNN

1 Introduction

With the popularity of location-based services in our lives, the demand for positioning and navigation is increasing. Although the Global Positioning System (GPS) performs well in outdoor positioning, it doesn't work effectively in indoor environments [1]. In daily life, we need to acquire the location information of indoor targets, such as in-door location information of large venues, and real-time location information of workers in high-risk working environment. Due to the widespread deployment of WiFi infrastructures, research on WiFi indoor positioning has become a hot spot, since its cost is relatively low and easy to implement.

Currently, research on WiFi indoor fingerprinting positioning begin to shift to using CSI instead of RSS [2]. Existing CSI indoor fingerprinting positioning method research shows that using CSI instead of RSS as the positioning signal source can further improve the positioning accuracy [3, 4]. Traditional CSI fingerprinting positioning method only considers the CSI signal amplitude information in specific directions at each reference location [5, 6]. In fact, during online stage, CSI data may be collected by

users face arbitrary directions. This may render mismatch between offline constructed fingerprints and online collected CSI data [7].

Considering the shortcomings of traditional CSI fingerprinting positioning method, we propose WiFi CSI fingerprinting positioning based on user rotation. Firstly, in the process of CSI data collection, the influence of human body absorption on the CSI signal amplitude is taken into account, and the CSI data is collected by the user turning around at each reference location. Secondly, in the process of online matching with fingerprints, different statistical features are selected to form the feature vectors for matching. Thirdly, we use the CSI from different APs to build a fingerprinting database and compare the impact of the number of APs on the positioning accuracy. Finally, the effectiveness of our method is verified by experiments. Compared with the traditional CSI fingerprinting positioning method, the CSI fingerprinting positioning system proposed in this paper has higher positioning accuracy and better stability.

The proposed positioning method is described in Sect. 2. Section 3 presents the experimental results and related discussions. Section 4 summarizes this paper.

2 Method Design

2.1 Fingerprinting Positioning Principle

Fingerprinting positioning method matches the online CSI feature vector with fingerprints, the method has two stages: offline stage and online stage, as shown in Fig. 1.

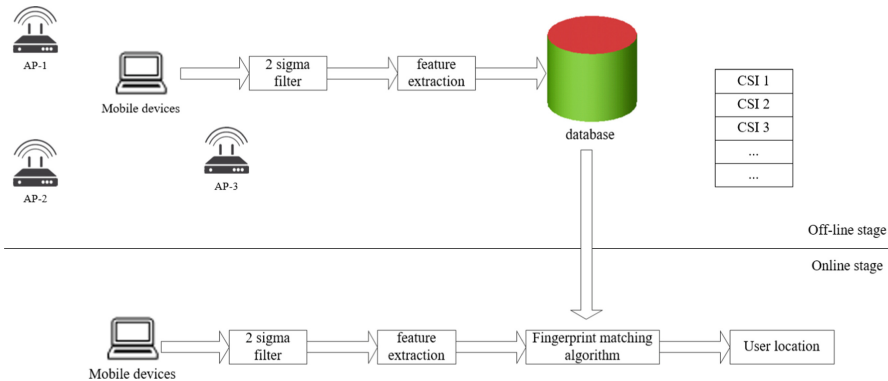


Fig. 1. Fingerprinting positioning principle.

In offline stage, we firstly divide the room area into n reference location, and collect CSI data at each reference location from m APs. Then, we extract the CSI signal amplitude from the collected CSI data, and use a filter to eliminate the disturbed CSI values. Finally, the statistical features of the filtered CSI signal amplitude are extracted to construct feature vectors. The feature vectors and related reference location coordinates are used to form a fingerprint. We use the *sigma* filter to eliminate disturbed CSI values. For the extraction of statistical features, we choose the minimum value, the

median value, the maximum value, the arithmetic mean value, the geometric mean value, and the harmonic mean value and standard deviation.

When collect data in the online stage, indoor environment must ensure is same as the fingerprint generate. We collect CSI data at user location. We eliminate the perturbation value and extract statistical features to form an online feature vector, and calculate the Euclidean distance with fingerprints. This can be obtained by the Euclidean distance formula (1):

$$dist_{ij} = \sum_{n=1}^{N_{ant} * N_{sub}} \sqrt{\mathbf{x}_i - \mathbf{x}_j} \quad (1)$$

Where $dist_{ij}$ is the Euclidean distance from the i -th user location to the j -th reference location in the fingerprint. \mathbf{x} denotes a feature vector, N_{ant} is the antennas number for collected CSI data, and N_{sub} is the subcarriers number of CSI data.

2.2 Fingerprint Matching Algorithm

In online stage, we use KNN algorithm to fingerprint matching positioning. The KNN algorithm is an improvement on the nearest neighbor (NN) algorithm. The first step of the KNN algorithm is to calculate the Euclidean distance from the user location CSI feature vectors with fingerprints. The second step is to sort the Euclidean distance from small to large (the smaller Euclidean distance, the higher similarity). The third step is to select the top K ($K \geq 2$) sorted Euclidean distance, and find the coordinate of the selected data. Finally, as shown in the formula (2), we will get user location by compute the mean of the coordinates corresponding to the K selected data.

$$(x, y) = \frac{1}{k} \sum_{i=0}^k (x_i, y_i) \quad (2)$$

Where (x_i, y_i) is the i -th selected reference location coordinate using KNN algorithm, and (x, y) is the result user location coordinate.

3 Experiment

3.1 Experimental Setup

In order to get CSI data, we chose Ubuntu 14.04.4 system notebook with Intel 5300 NIC. According to the MIMO protocol, subcarriers between antennas don't interfere with each other, therefore, 30 subcarriers can be combined as experimental data. In the experiment of this paper, we chose a 70 m² room. According to the actual environment in the room (table location, whether the CSI data is convenient to collect), we set twenty-four reference locations, ten user locations and three APs. Figure 2 shows the indoor environment layout.

We collect CSI data using two methods, the proposed method in this paper and the traditional method. In the proposed method, we consider the influence of human body absorption on CSI signal amplitude, and collect CSI data by user rotation in each

reference location. In the traditional method, we collect CSI data in four directions (0° , 90° , 180° , 270°) at each reference location.

3.2 CSI Data Analysis

Through the study of CSI signal amplitude feature vectors, we found that the CSI signal amplitude is related to location and direction. In theory, the line-of-sight (LOS) path wireless signal have a large signal strength, and the CSI signal amplitude is low. On the contrary, the non-line-of-sight (NLOS) path wireless signal strength is small, and the CSI signal amplitude is high. When the user holds the notebook in front of the chest to receive CSI data, the CSI signal amplitude will change with different directions because of the influence of human body absorption on CSI signal amplitude.

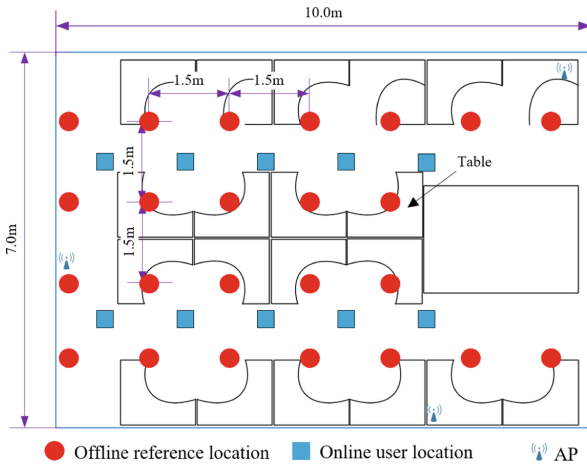


Fig. 2. Indoor environment layout.

We collect CSI data by user rotates three times in one location. It can be seen from Fig. 3 that the CSI signal amplitude periodically change three times during the user rotation three times. Figure 3(a) show the raw CSI signal amplitude. We can be seen that there are some disturbed value, so we use 2 sigma filter to process raw data. The filtered data is shown in Fig. 3(b).

3.3 Positioning Accuracy Comparison

According to the experiment setup in Sect. 3.1. Using our method, we collect CSI data from three AP in each reference location to generate a fingerprint. In online stage, we use KNN algorithm to estimate the location of twenty online samples. Then analyze mean positioning errors by using different AP numbers, we can get that the mean positioning error using one AP is 2.34 m, using two APs is 2.04 m and using three APs is 1.58 m.

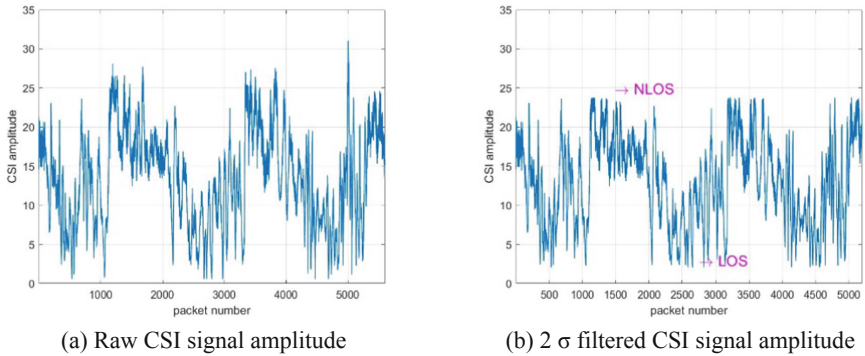


Fig. 3. CSI single amplitude variations of user rotation three times.

As shown in Fig. 4, it can be seen that the positioning accuracy is significantly improved as the number of AP increases. The reason is that when use one or two APs collecting CSI data, the positioning error may occur at the same radius around the AP. In Fig. 4, we can also see the influence of the parameter K on the positioning accuracy. We use KNN algorithm to choose the K location with the smallest Euclidean distance as the user location neighborhood cluster. Finding the mean of the coordinates corresponding as the user location. As the parameter K increases, it can be seen that the KNN algorithm positioning accuracy first becomes higher and then becomes lower. When K is equal to four, the positioning error is the smallest, and equal to 1.58 m.

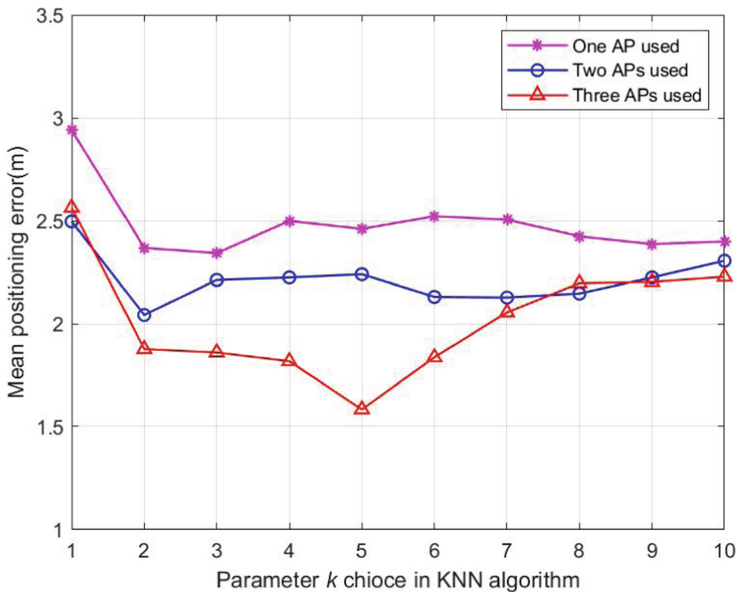


Fig. 4. Positioning error of the user rotating fingerprint under different AP numbers.

Now we use three APs positioning results to compare the accuracy. Using our method and traditional method, we collect CSI data from three AP in each reference location to generate two fingerprints. The positioning error of two methods is shown in Fig. 5.

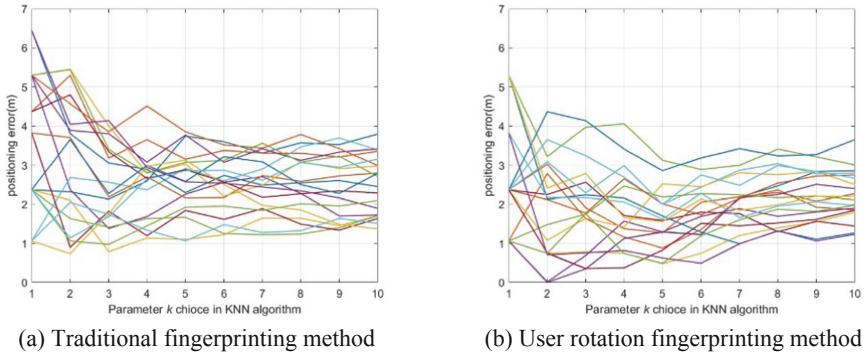


Fig. 5. Positioning error of two methods for twenty test samples.

Figure 5(a) shows the positioning results of the Traditional fingerprinting method. It can be seen that the positioning error of twenty test samples is 2–4 m. Figure 5(b) shows the positioning results of our method. We can see that the positioning error of twenty test samples distribute at 0.5–3 m. The mean positioning error of twenty samples is shown in Fig. 6.

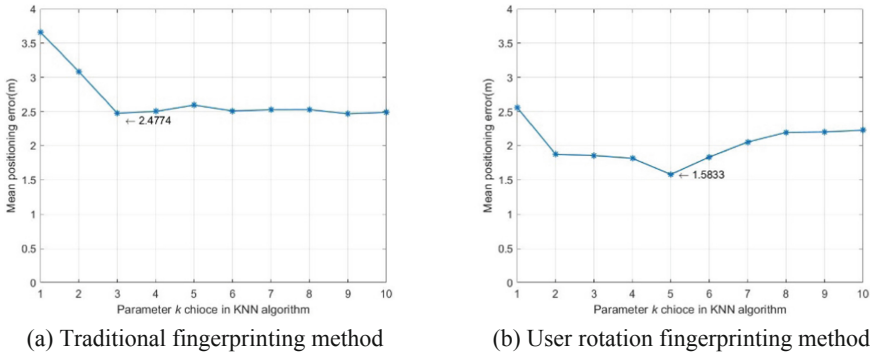


Fig. 6. Mead positioning error of two methods for twenty test samples.

We can see that the minimum positioning error of traditional fingerprinting method is 2.48 m. The minimum value of the local mean error of our method is 1.58 m. Our method reduces the positioning error by 36.3% compared with the traditional method. In Fig. 6(a), we can see that traditional fingerprinting method has minimum positioning

error when K value is three, and in Fig. 6(a) when the K value is five our method has minimum positioning error. By analyzing the positioning results of the two methods and selecting the K value with the highest positioning accuracy, we can obtain Table 1.

Table 1. Comparison of positioning errors between two methods.

	Traditional method	Proposed method	Error reduction rate
Max error (m)	4.14	3.13	24.4%
Mean error (m)	2.48	1.58	36.3%
Media error (m)	2.32	1.57	32.3%
Min error (m)	0.79	0.48	39.2%

It can be seen from Table 1 that compared with the traditional method, the proposed method of this paper reduces the maximum positioning error by 24.4%, the mean error by 36.3%, the median positioning error by 32.3% and the minimum positioning error by 39.2%. In addition to some large positioning errors caused by some environmental factors, the positioning accuracy of our method is significantly improved.

4 Conclusions

In this paper, we introduce a CSI fingerprinting positioning method, which considers the influence of human body absorption on CSI signal amplitude. We collect CSI data by user rotation in each CSI collected location. The positioning results indicate that compared with the traditional method, the proposed method in this paper reduces the mean positioning error by 39.1%.

References

1. Wang, Z., Chen, Y., Wang, H.: Sequence-based indoor localization with channel status information. *IEEE Sens. J.* **18**(6), 1817 (2018)
2. Deng, Z.A., Hu, Y., Yu, J., et al.: Extended Kalman filter for real time indoor localization by fusing WiFi and smartphone inertial sensors. *Micromachines* **6**(4), 523–543 (2015)
3. Fang, S.H., et al.: Channel state reconstruction using multilevel discrete wavelet transform for improved fingerprinting-based indoor localization. *IEEE Sens. J.* **16**(21), 7784–7791 (2016)
4. Wang, X., Gao, L., Mao, S., et al.: CSI-based fingerprinting for indoor localization: a deep learning approach. *IEEE Trans. Veh. Technol.* **66**(1), 763–776 (2017)
5. Shi, S., et al.: Accurate location tracking from CSI-based passive device-free probabilistic fingerprinting. *IEEE Trans. Vehic. Technol.* **PP**(99), 1 (2018)
6. Song, Q., et al.: CSI signal amplitude fingerprinting based NB-IoT indoor localization. *IEEE Internet Things J.* **5**(3), 1494–1504 (2018)
7. Zhou, M., Tang, Y., Nie, W., et al.: GrassMA: graph-based semi-supervised manifold alignment for indoor WLAN localization. *IEEE Sens. J.* **17**(21), 7086–7095 (2017)