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Hierarchical CSI-Fingerprint Classification for Passive Multiperson Localization

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Indoor human localization is an important enabling technology for several intelligent applications. One advantage of a passive localization algorithm is that it can estimate human location without requiring the user to carry an electronic device. Because of complex signal radiation in indoor environments, most localization algorithms adopt the fingerprint approach for indoor passive localization. Fingerprints can enable good performance in single-person passive localization. However, when more than two people are in the target area, the system performance may degrade due to the high complexity of the fingerprint-matching task. In this paper, a hierarchical channel state information (CSI)-fingerprint classification system is proposed for passive indoor multiperson localization. In the training phase for coarse classification, fingerprints with similar CSI are first grouped into coarse classes. Then, a coarse classifier is trained for coarse fingerprint matching. Fingerprints belonging to the same coarse class are then entered into a fine classifier for fine fingerprint matching. Experimental results revealed that the proposed approach achieved good accuracy in 93 configurations involving zero to three people. Furthermore, CSI grouping shows that the similarity of CSI depends on the line-of-sight and the number of people.

Keywords: CSI fingerprints, multiperson localization, device free localization, hierarchical classification, quadratic discriminant analysis

1. INTRODUCTION

Indoor localization is important for applications such as indoor navigation systems in large shopping malls, alarm systems in smart homes, and home healthcare for the elderly [1]. Positioning technologies are categorized as active and passive localization systems depending on whether the user is required to carry a device. In active localization, the user must carry special electronic devices, such as a cellphone or e-tag. The electronic devices then transmit or receive singles from anchor points with known locations to assist the calculation of the location. If the person forgets to carry the device, the system malfunctions. By contrast, because the user is not required to carry a device, they will feel conformable during the operation of the passive localization system [2]. Furthermore,

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an inexpensive commercial off-the-shelf wireless fidelity (Wi-Fi) network interface card (NIC) can be used directly for passive localization. Therefore, passive localization is a promising technology for indoor localization.

Complex indoor radio-signal propagation renders the received signal strength indicator (RSSI) unsuitable for indoor locations because of the large variations in the indicator [3]. By contrast, low-level physical layer channel state information (CSI) [3] is a relatively stable indicator. For a configuration with specific people and locations as well as a person standing at a specific location, the extracted CSI of a Wi-Fi link can be considered as a fingerprint [4, 5]. CSI fingerprints corresponding to different locations are stored in offline databases. For a new physical configuration in a target area, the configuration can be recovered by first extracting the CSI value of the Wi-Fi link as a new fingerprint and then matching the new fingerprint with the stored fingerprints.

Because of the high complexity of multiperson localization, current indoor passive localization systems can only provide single-person localization. However, many applications involve more than one person. If the positions of multiple people can be identified simultaneously, then the location-based service can be realized to provide innovative smart applications. For example, it is difficult for elderly people to carry a device for healthcare applications. Therefore, passive localization systems, in which only a Wi-Fi communication link is required to estimate the location of elderly people, can be used to overcome this problem. The objective of this paper is to explore the characteristics of an indoor multiperson localization problem (MLP) and propose a mechanism to resolve this problem. The major challenges of MLP are summarized as follows:

1. *Complexity:* The combination of possible configurations increases drammatically with the number of people. Moreover, fingerprint matching in a large database is a challenging problem.
2. *Human body signal absorbency:* Different human bodies absorb and reflect different amounts of radio signal. People standing at different locations should be considered as different configurations even if the number of people and the occupied locations are the same. For example, if two people switch locations, a new configuration should be recognized.

In this paper, a coarse-to-fine classification algorithm is proposed to overcome the challenges of indoor multiperson localization. The major contributions of this paper are as follows:

1. A coarse-to-fine hierarchical classification algorithm is proposed to resolve the high complexity of multiperson localization.
2. The relationship between peoples' locations and CSI values is explored.

The remainder of this paper is organized as follows. In Section 2, studies of indoor localization are briefly described. Section 3 provides the background for this study. The proposed hierarchical CSI classification method for multiperson localization is presented in Section 4. Section 5 provides preliminary experimental results for this method. Finally, Section 6 concludes this paper.

2. RELATED STUDIES

Localization algorithms are categorized into active and passive localization depending on whether the user is required to carry an electronic device. Previous works on active and passive localization are briefly described as follows.

2.1 Active Localization

Localization algorithms that require users to carry electronic devices are classified as active localization algorithms. Active localization algorithms can be further categorized into range-based [6] and range-free [7] approaches. In the range-based positioning mechanism, the distance is estimated through time delays, radio propagations, or other distance measurement techniques. On the basis of the distances between localization targets and the positions of anchor points, the unknown position of a target can be estimated through triangulation. In the range-free localization mechanism, only coverage information is provided, and distance information is unavailable. The position of a target can be estimated through the intersection of the coverage areas of multiple anchor points. However, requiring the user to carry a device considerably restricts the potential applications of active localization.

2.2 Passive Localization

Passive localization algorithms are categorized into RSSI- and CSI-based mechanisms. In RSSI-based passive localization mechanisms, the measured RSSI differs when the target is in different locations. By matching the RSSI fingerprint with the stored fingerprints in the database, the corresponding location of the targets can be retrieved. However, the variations in RSSI degrade the accuracy of the RSSI-based passive localization algorithm [3]. By contrast, a CSI-based approach utilizes the physical layer CSI of a wireless communication link. When a target is at a particular location, the corresponding CSI can be measured. The CSI-fingerprint matching algorithm can be applied to determine the location of the target. Compared with RSSI methods, CSI-based approaches exhibit good stability [8]. Therefore, the CSI-based approach can be used to achieve a higher positioning accuracy than can the RSSI-based approach. Indoor multiperson localization is a challenging problem. Some approaches require the localization targets to carry an electronic device or RFID tag [9], whereas others apply computer vision technology [10, 11]. The approach proposed in [12] achieved passive multiperson localization; however, this system relied on a custom antenna system, which restricts the potential applications of this type of localization. Passive multipeople localization is a challenging research problem [12]. Only few active localization methods have been proposed in the literature [9]. To the best of our knowledge, no previous studies have focused on the passive multipeople localization problem. The contribution of this manuscript is two-fold. First, CSIs with high similarities are grouped and can be investigated to reveal the relationship between the physical locations of people and CSI similarities. Second, a divide and conquer approach is proposed to overcome the large classes classification problem inherited in for passive multipeople localization.

3. BACKGROUND

3.1 Orthogonal Frequency Division Multiplexing

Orthogonal frequency division multiplexing (OFDM) technology [13] divides a large spectrum into multiple subcarriers. Almost no interference exists between two neighboring subcarriers, and a large symbol duration can be applied to mitigate the multipath fading problem; thus, OFDM has been widely applied in modern wireless communication systems, such as Wi-Fi, worldwide interoperability for microwave access (WiMAX), and long term evolution. In a wireless communication link, each subcarrier experiences different fading; therefore, the OFDM technology can provide rich CSI in the physical layer and is suitable for passive localization.

3.2 Channel Impulse Response and Channel Frequency Response

The channel impulse response (CIR) [8] can be used to describe the characteristics of a communication link. If the transmitter sends a pulse signal, the receiver may receive a composite signal that is a combination of multiple signals traveling along different paths. This can be formulated as a time-domain linear filter as follows:

$$h(\tau) = \sum_{i=1}^{N} | a_i | e^{-j\theta_i} \delta(\tau - \tau_i). \tag{1}$$

In Eq. (1), a_i, θ_i, and τ_i denote the amplitude, phase shift, and time delay of the ith path, respectively, where N is the total number of paths and $\delta(\cdot)$ is a delta function. Restricted by the bandwidth of the system, the ability to distinguish multiple paths is limited by the system time resolution.

In the frequency domain, the OFDM technology provides a sampled version of the channel frequency response (CFR) as follows:

$$H(f) = [H(f_1), H(f_2), \ldots, H(f_k)], \tag{2}$$

where $H(f_k)$ is a complex number that represents the magnitude and phase of CFR at frequency f_k. The CIR can be converted into CFR using a Fourier transform, as shown in Eq. (3).

$$H(f) = FFT(h(\tau)) \tag{3}$$

Leveraging the commercial off-the-shelf Intel 5300 NIC with a publicly available driver as in [14], a group of CFRs with k = 30 subcarriers is exported to upper layer user applications in CSI format. CSI data has been applied in many human-computer interaction problems [15], such as keystroke recognition [16], emotion recognition [17], motion recognition [18], speed estimation [19], and activity recognitions [20, 21]. In this paper, CSI data is applied to the passive indoor MLP.

4. PASSIVE MULTIPERSON LOCALIZATION

4.1 Complexity of the Multiperson Localization Problem

Numerous CSI passive localization technologies have adopted fingerprinting to determine location. When multiple people are in the target area, the size of the fingerprint library increases considerably because the permutations and combinations of human bodies in different regions generate numerous configurations. The costs of offline training and online matching also increase. Assuming p locations and a maximum of n people in the target area, the total number fingerprints $S(p, n)$ can be calculated as

$$S(p, n) = C_0^p + C_1^p + \ldots + C_n^p, \tag{4}$$

where C_k^p is k-combination with a set of size p. C_k^p is calculated as in Eq. (5):

$$C_k^p = \frac{p!}{(p-k)!k!}. \tag{5}$$

In a target area comprising a maximum of n individuals, there may be $n-1$, $n-2$, ..., 1, 0 people in the target area. No one in the target area is represented by C_0^p.

Whenever the value of n is increased by 1, a new combination term is added to S, as shown in Eq. (5). Table 1 shows the number of fingerprints associated with various values of n; for example, when p is 8, $n \leq (p/2)$. Table 1 reveals that when the target area has eight measurement points and a maximum of four people within the area, the number of fingerprints has 163 different classes. With such a large number of fingerprints, both system accuracy and matching time pose a challenge. When the system makes distinguishes between different people, the fingerprint record $S^*(p, n)$ will be larger than $S(p, n)$.

$$S^*(p, n) = P_0^p + P_1^p + \ldots + P_n^p, \tag{6}$$

where $P_k^p = \frac{p!}{(p-k)!}$. Because of the high complexity of the MLP, implementing such a system is challenging. This paper adopts a coarse-to-fine approach to overcome this problem. Similar CSI fingerprints are first grouped to train a coarse classifier, and multiple fine classifiers are then trained to classify detailed CSI fingerprints.

Table 1. Number of combinations with various n when p = 8.

n	0	1	2	3	4
S	1	9	37	93	163

4.2 Symbol Definitions

The symbol definitions for hierarchical fingerprints classification are summarized as in Table 2.

Table 2. Symbol definitions.

Symbol	Description
x_i	CSI vector of pattern i.
y_i	Fine class label of pattern i.
c_i	Coarse class label of pattern i.
μ_j	Mean vector of samples x_i belonging to fine class j.
$\phi(j, k)$	A mapping function between fine class j and coarse class k. $\phi(j, k) = 1$ if fine class j belongs to coarse class k, and 0 otherwise.
M_0^{coarse}	Coarse QDA-based model.
M_c^{fine}	Fine QDA-based model for coarse class c.
N	Total number of samples
N_j	Number of samples in fine class j.
P	Total number of fine classes.
P_k	Number of fine classes in coarse class k.
K	Total number of coarse classes.

4.3 Coarse Classification

The essence of fingerprint matching is a classification problem. During classification, input data is marked with a correct label by the classifier, indicating a correct fingerprint match. When the number of classes is high, it is difficult to use a single classifier to correctly classify all fingerprints. A divide and conquer approach is proposed to overcome this complex classification problem. All samples are first grouped into a small number of coarse classes according to the similarities between samples. A coarse classifier is then trained to classify patterns into coarse classes. Finally, a fine classifier is trained to classify patterns into fine classes. Because the number of classes within a coarse class is less than the original number of classes, it is a simpler classification problem than the original one. Because the search space in fine classes is smaller than that in the original problem, this approach does not increase the amount of calculation, and the overall matching time can thus be reduced. The overall system accuracy is bounded by the accuracy of both coarse and fine classifiers. In particular, the accuracy of the coarse classifier dominates the overall performance. Therefore, designing a high accuracy classifier is important for obtaining a successful hierarchical fingerprint-matching algorithm.

Coarse classification is conducted using an unsupervised k-means algorithm to achieve offline sample clustering and the k-nearest neighbor classifier in the online stage. Within each coarse class, the quadratic discriminant analysis (QDA) classifier is trained to perform fine fingerprint matching. QDA is briefly introduced as follows, after which the details of the training and test phases of coarse classification are presented.

(A) Quadratic Discriminant Analysis

To achieve accurate fingerprint-matching results, a high-performance classifier is required. QDA [22] is a statistical classification technique that is closely related to the well-known linear discriminant analysis (LDA) [23]. However, in QDA, there is no assumption that the covariance of each class is identical.

To perform QDA, the covariance matrix $\sum_k$ of each class k is first computed, where $k = 1, 2, 3, \ldots, K$ denote the classes, and K is the total number of classes. The quadratic discriminant function is defined as

$$\delta_k(x) = -\tfrac{1}{2}\log|\Sigma_k| - \tfrac{1}{2}(x-\mu_k)\textstyle\sum_k^{-1}(x-\mu_k) + \log\pi_k \tag{7}$$

where $|\cdot|$ denotes the determinants, π_k is a prior probability, and μ_k represents the mean vector.

The discriminant function in Eq. (7) is a quadratic function. The classification rules can be denoted as

$$\hat{G}(x) = \arg\max_k \delta_k(x) \tag{8}$$

where pattern x belongs to the class $\hat{G}(x)$, which has a maximum value of $\delta_k(x)$.

(B) Training Phase

In the training phase of coarse classification, all training samples are clustered using an unsupervised k-means learning algorithm. The operations of the k-means algorithm are summarized as follows:

1. Randomly choose K samples as the initial cluster centroid.
2. For each sample, calculate the distances to all cluster centroids. Then, find the cluster with minimum distance to this point and assign the sample to this class.
3. For assigning the new cluster membership, use the average method to recalculate the clustering center.
4. Repeat steps 2 and 3 until the algorithm convergence (the center point has no change or the cluster membership has no change).

By using the k-means algorithm, a mapping function $\phi(j, k)$ can be obtained, where $\phi(j, k) = 1$ if any sample of fine class j belongs to coarse class k and $\phi(j, k) = 0$ otherwise. A fine class can belong to more than one coarse class. On the basis of the results of the k-means algorithm, pattern x_i is given a new coarse class label c_i. All samples x_i and their corresponding coarse class label c_i are applied to train the k-nearest neighbors (k-NN) coarse classifier M_0^{coarse}, which is used to match the patterns to the coarse classes. The training set for the coarse classifier is $T = \{(x_i, c_i) \mid \text{for } i = 1, \ldots, N\}$.

(C) Test Phase

In the test phase of coarse classification, a new CSI vector x' is classified using the coarse classifier to determine which coarse class it belongs to, that is,

$$c' = M_0^{coarse}(x'). \tag{9}$$

Then, pattern x' is classified as the coarse class c'.

4.4 Fine Classification

After coarse classification, classes within the same coarse class are distinguished to find the true class. Because the number of classes within a coarse cluster is less than the original number of classes, the classification task within a coarse cluster is simpler than the original classification problem. Several classification algorithms can be used to achieve fine classification, such as LDA, QDA, k-NN, support vector machines, and earth mover's distance (EMD) [24]. The input and output formats of various classification algorithms are heterogeneous; therefore, it is necessary to transform the format of data and extract features in the training phase to achieve strong performance. Therefore, in this paper, the QDA is applied to justify the overall system performance.

(A) Training Phase of Fine Classification

In the training phase of fine classification, a separate fine classification model M_k^{fine} is trained for each coarse class k. For coarse class k, the training data set is extracted from the original training set as follows: $T_k = \{(x_i, y_i) \mid \phi(y_i, k) = 1, \text{ for } i = 1, \ldots, N\}$.

(B) Test Phase of Fine Classification

In the test phase of fine classification, the unknown input CSI vector x' is first entered into the coarse classification model M_0^{coarse} to determine the coarse class c', as shown in Eq. (9). Then, the corresponding fine classification model $M_{c'}^{fine}$ is applied to determine the final class y', that is,

$$y' = M_{c'}^{fine}(x'). \tag{10}$$

The unknown input vector x' is finally classified as fine class y'.

4.5 Time Complexity Analysis

To evaluate the time cost of the proposed method, time complexities in both the training and test phase are provided as follows. Let d denote the number of subcarriers in a CSI sample, N_t denote the number of training samples, N_r denote the number of test samples, K denote the number of multiperson configurations, and c denote the number of coarse classes. In the training phase, the major computational tasks include the k-means algorithm, k-NN classifier training, and QDA fine classifiers training. The time complexity of the k-means algorithm is $\boldsymbol{O}(N_t K\, d\, I)$, where I is the number of iterations executed by the k-means algorithm. In the training phase, the cost of the k-NN classifier is $\boldsymbol{O}(1)$. Assuming that the samples are evenly distributed into K clusters and that the expected number of duplications of each configuration is R, the time complexity of QDA fine classifier training is $\boldsymbol{O}(N_t\, d^2)$. Therefore, the time complexity in the training phases is given as

$$T_{training} \in \boldsymbol{O}(N_t K d I) + \boldsymbol{O}(1) + K \times \boldsymbol{O}(\tfrac{R}{K} N_t d^2).$$

In the test phase, the major computational tasks include k-NN classifier recall and QDA classifier recall. Thus, the time complexity in test phase is given as

$$T_{recall} \in \boldsymbol{O}(N_t d) + \boldsymbol{O}(N d^2).$$

5. EXPERIMENTAL RESULTS

5.1 Experimental Setup

To justify the performance of the proposed hierarchical CSI-fingerprint matching algorithm, an experiment comprising eight measurement points and a maximum of three people was conducted. Table 1 shows that the combination of eight points and three people had 93 configurations. The layout of these eight measuring points is shown in Fig. 1. The distance between two neighboring points in the same direction was 1m. The ground height of Access Point (AP) was approximately 2 m and the measurement points were labeled from 01 to 14, as shown in Fig. 1. The details of the 93 configurations are summarized in Table 3. The signal transmitter used was a Kingston MobileLite Wireless, and the signal receiver was a mini PC equipped with Intel 5300 NIC. CSITools running on Ubuntu Linux was used for data collection. The acquisition rate was approximately 20 packets/s. For each configuration, the CSI data extraction lasted for 75s and approximately 1500 complex numbers were extracted. The raw complex number was transformed to extract the amplitude information in each subcarrier for fingerprint matching. We used the first 1000 samples of amplitude data as the training set and the final 500 samples of amplitude data as the test set. To mitigate signal noise for both training and test sets, 40 successive samples were averaged. Because of the limited number of samples, partial overlapping was allowed to enable calculation of the training and test samples. However, there was no overlapping between the training and test samples. Thus, for each configuration, 40 training samples and 20 test samples were generated. Because there were 93 configurations, the total numbers of training and test samples were 3720 and 1860, respectively.

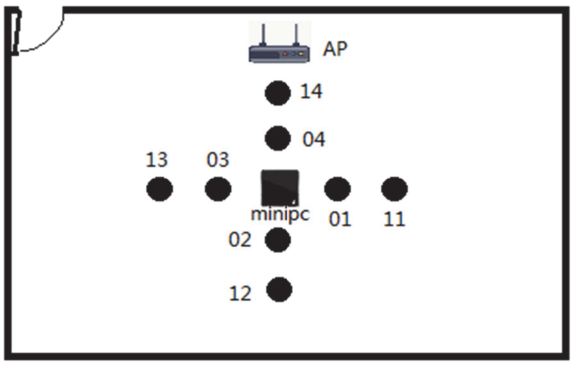

Fig. 1. Layout of the eight measurement points in the experiment.

5.2 Coarse Classification Results

In the coarse classification phase, the samples in 93 configurations were grouped into six coarse clusters using the *k*-means algorithm. After determining these six categories, the *k*-NN classifier was trained to classify the training samples into these six categories. The membership relations were then established using the coarse classifier operated

Table 3. The 93 location configurations for passive localization experiments with three people and eight measurement points.

	Measurement Points									Measurement Points									Measurement Points							
	01	02	03	04	11	12	13	14		01	02	03	04	11	12	13	14		01	02	03	04	11	12	13	14
1									32		v	v		v				63					v	v		v
2	v								33		v	v			v			64					v		v	v
3		v							34		v	v				v		65						v	v	v
4			v						35		v	v					v	66	v	v						
5				v					36		v		v	v				67	v		v					
6					v				37		v		v		v			68	v			v				
7						v			38		v		v			v		69	v				v			
8							v		39		v		v				v	70	v					v		
9								v	40		v			v	v			71	v						v	
10	v	v	v						41		v			v		v		72	v							V
11	v	v		v					42		v			v			v	73		v	v					
12	v	v			v				43		v				v	v		74		v		v				
13	v	v				v			44		v				v		v	75		v			v			
14	v	v					v		45		v					v	v	76		v				v		
15	v	v						v	46			v	v	v				77		v					v	
16	v		v	v					47			v	v		v			78		v						v
17	v		v		v				48			v	v			v		79			v	v				
18	v		v			v			49			v	v				v	80			v		v			
19	v		v				v		50			v		v	v			81			v			v		
20	v		v					v	51			v		v		v		82			v				v	
21	v			v	v				52			v		v			V	83			v					v
22	v			v		v			53			v			v	v		84				v	v			
23	v			v			v		54			v			v		v	85				v		v		
24	v			v				v	55			v				v	v	86				v			v	
25	v				v	v			56				v	v	v			87				v				V
26	v				v		v		57				v	v		v		88					v	v		
27	v				v			v	58				v	v			v	89					v		v	
28	v					v	v		59				v		v	v		90					v			v
29	v					v		v	60				v		v		v	91						v	v	
30	v						v	v	61				v			v	v	92						v		v
31		v	v	v					62					v	v	v		93							v	v

on the training samples. If the samples of the configuration were classified into coarse class C_k, then this configuration was assigned as a member of C_k. To increase the accuracy of the coarse classification, a configuration can belong to more than one coarse classes. In the test phase, the accuracy of coarse classification was 97.42%. The membership relation between coarse and fine classes is given in Table 4. To demonstrate the performance of coarse classification, the confusion matrix of test samples in the coarse classification is shown in Table 5.

5.3 Fine Classification Results

The QDA classifier was applied to achieve fine classification. The aim of fine classification is to discriminate the fine classes within a coarse class. The accuracies of fine classification for the six categories in the training and test phases are shown in Table 6, which reveals that the QDA classifiers have high accuracy in the training phase, but the performance is reduced in the test phase. The overall performance of the proposed hierarchical fingerprints matching algorithm was 84.76%.

Table 4. Membership relation of coarse and fine classes after the coarse classification phase.

Coarse class	Fine classes
C_1	5,8,9,14,50,51,52,54,66,67,75,77
C_2	7,11,13,22,25,29,31,32,33,34,35,36,37,38,39,40,41,42,43,44,47,53,56,59,62, 65,73,81,85,89,92
C_3	2,10,11,13,15,16,20,21,22,23,26,27,29,30,31,46,47,48,49,53,55,58,60,61,64, 68,71,72,79,81,82,83,86,90,93
C_4	3,7,11,12,13,18,26,28,31,32,33,34,36,40,41,42,43,44,45,53,56,59,60,62,63,65, 70,74,76,77,78,88,91,92
C_5	1,2,4,6,7,10,11,12,13,14,15,16,17,18,19,20,21,24,26,27,28,29,30,46,49,53,55, 57,58,60,61,64,68,69,70,71,72,73,75,76,77,78,79,80,82,84,86,87,89,93
C_6	1,4,5,6,8,9,10,12,14,17,19,20,26,28,46,50,51,52,54,55,57,60,61,63,64,66,67, 69,75,76,77,78,80,86,87,89

Table 5. Confusion matrix after coarse classification for six coarse classes.

Actual Value \ Result	C_1	C_2	C_3	C_4	C_5	C_6
C_1	117	0	0	0	0	0
C_2	0	317	6	0	0	0
C_3	0	0	257	2	9	2
C_4	0	18	6	369	0	6
C_5	0	0	6	1	426	5
C_6	0	0	1	5	3	304

Table 6. Accuracy of fine classification in each coarse class for training and test phases.

Rate	Coarse Classes					
	C_1	C_2	C_3	C_4	C_5	C_6
Training Phase	99.4%	96.8%	96.9%	96.2%	97.2%	98.5%
Test Phase	99.1%	85.9%	88.4%	83.0%	89.3%	93.6%

5.4 Comparison With the State-of-the-art EMD Fingerprint Matching

To justify the performance of the proposed hierarchical CSI-fingerprint classification mechanism, the state-of-the-art EMD fingerprint-matching algorithm [8, 24] was chosen for comparison. The EMD can preserve statistical characteristics in the frequency domain of CSI information and has a stable performance. The EMD-based CSI matching experiment was executed as follows. In the model construction phase, CSI samples for each physical configuration and different target positions were extracted for a duration of 1 min. More than 1000 samples can be extracted within this duration. Each sample includes three antennas and each antenna contains 30 subcarriers. Ninety histograms of those 1000 samples were considered as model fingerprints and stored in the fingerprint database. In the matching phase, histograms of 100 samples (approximately 5s) or 50 samples were considered as test fingerprints. The test fingerprints were then compared with all model fingerprints individually. The model fingerprints with minimum EMD were considered as the best match. The physical configuration corresponding to the best matching model fingerprints was output as the position result. The simulation results are shown in Table 7.

Table 7. Results of EMD-based fingerprint-matching.

Sample Size	Correct Matching Rate		
	Ant. 1	*Ant.* 2	*Ant.* 3
50	62.97%	61.35%	65.68%
100	69.73%	69.73%	69.73%

Table 7 shows that the best correct matching rate of the EMD-based fingerprints matching algorithm for the indoor MLP was 69.73%. Furthermore, a duration of more than 5 s was required for EMD to obtain a sufficient number of samples to construct the test fingerprints. However, in the proposed hierarchical CSI-fingerprint classification algorithm, only 40 samples (2s) were required to obtain the test sample x', and a higher matching accuracy of 84.76% was achieved.

6. CONCLUSION

This paper addresses the problem of passive multiperson localization by emplyoing CSI and proposes a coarse-to-fine classification mechanism to reduce the complexity of multiperson localization. Moreover, CSI coarse classification is used to analyze the association between CSI and multiperson configuration. The validity of the hierarchical classification method is verified through experiments. The MLP cannot be fully resolved using this technique; moreover, increasing the number of people or the number of measurement points results in new challenges for the fingerprint method. In the future, we will attempt effective feature extraction of the fingerprints and investigate the generalization ability of various classification algorithms in both coarse and fine classifications.

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