Single-Site Hybrid Positioning System Based on LOS Recognition

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***Abstract*—The indoor environment is much more complicated than the outdoor environment, which brings huge challenges to localization. In order to improve the accuracy and reliability of the indoor positioning system, we propose a single-site *hybrid positioning* (HP) system based on LOS recognition in this paper. The system adopts different positioning methods for different situations by distinguishing whether there is a *line-of-sight* (LOS) path in the environment. In this system, a LOS recognition algorithm is firstly designed to judge the LOS path depending on the received *channel state information* (CSI). According to the LOS recognition result, the HP system adaptively selects the optional positioning algorithm. When there is a LOS path, the positioning method based on parameter estimation is applied for localization. When there is no LOS path, a fingerprint-based positioning algorithm is proposed. Mean filtering and *priciple component analysis* (PCA) are used to do data dimensionality reduction and a combination of *neural network* (NN) and *weighted k-nearest neighbour* (WKNN) is used to complete position estimation. Finally the HP system is compared with other positioning systems, and the experimental results show that our proposed HP system can achieve higher positioning accuracy.**

***Keywords*—channel state information, hybrid positioning, line-of-sight recognition, single-site positioning**

I. Introduction

Localization is the core technology of *location-based services* (LBS). At present, *global navigation satellite system* (GNSS) is the most important outdoor positioning system. However, because satellite signals are easily blocked by buildings and walls in the complex indoor environment, the signal quality drops sharply, resulting in large positioning error [1]. Therefore it is very important to study related positioning algorithms to improve indoor positioning accuracy [2].

At present, the indoor positioning systems can be roughly divided into two types: *parameter estimation-based positioning* (PBPE) and *fingerprint-based positioning* (FBP). The PBPE system estimates the parameters of propagation delay and incident angle and calculates the position of the device based on these ranging parameters through geometric methods [3]–[5]. The PBPE system often requires a *line-of-sight* (LOS) path between the transmitter and the receiver [6]. When there is no LOS path, the signals are reflected and scattered due to the obstacles, resulting in large error bias of the positioning parameter estimation. The PBPE system will have poor positioning performance and is not suitable for positioning in such situation. To deal with this problem, the FBP system is generally used [7]. The FBP system estimates the position of the device depending on the correlation between the wireless signals and the location points. For example, Chen et al. achieve *channel state information* (CSI)-based positioning through a probabilistic method [8]. There are also many CSI-based systems which implement position estimation through *neural network* (NN) classification [9], [10]. The FBP system is less affected by the environment and has higher robustness in the *none-line-of-sight* (NLOS) environment.

In this paper, we propose a single-site *hybrid positioning* (HP) system based on LOS recognition. The HP system adopts different positioning methods for different LOS conditions. This system is composed of three parts: LOS recognition, FBP method and PBPE method. In the LOS recognition algorithm, a new feature is constructed to complete LOS recognition simply and effectively. According to the result of LOS recognition, the PBPE method and the FBP method are respectively applied for localization. In the PBPE method, the *multiple signal classification algorithm* (MUSIC) is applied to estimate the ranging parameters. In the FBP method, *mean filtering* (MF) and *principal component analysis* (PCA) are used to do noise reduction and data dimensionality reduction and a combination of NN and *weighted k-nearest neighbour* (WKNN) is applied to achieve position estimation. Finally we have compared our proposed HP system with other positioning systems, and the results show that the HP system can achieve higher positioning accuracy. The contribution of this paper are as follows.

1) We propose a single-site HP system based on LOS recognition, which achieves high positioning accuracy.
2) We propose a LOS recognition algorithm, which uses CSI as input data and constructs a new feature to complete LOS recognition simply and effectively.
3) We propose a PBPE method that uses MF and PCA to reduce data dimensionality, and uses a combination of NN and WKNN to achieve position estimation.

Following the introduction, we will describe the HP system in details in Section II. The experimental results are analyzed in Section III. Finally, the conclution is drawn in Section IV.

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II. THE HYBRID POSITIONING SYSTEM BASED ON LOS RECOGNITION

In order to give full play of the advantages of the FBP method and the PBPR method, the HP system is designed to improve the indoor positioning accuracy in this paper. According to the result of LOS recognition, the HP system adaptively selects the optional positioning algorithm. As shown in Fig. 1, the system consists of three parts: LOS recognition, FBP method and PBPE method.

A. LOS Recognition Scheme

The purpose of LOS recognition is to judge whether there is a LOS path. In the HP system, different methods are applied for localization according to the result of the LOS recognition.

Considering the CSI contains rich information of the channel, the channel characteristics are analyzed in both time and frequency domain and are extracted to recognize the LOS path. In this paper, a new feature is constructed to complete LOS recognition simply and effctively. The LOS recognition scheme can be divided into two parts: new feature construction and recognition algorithm.

1) New Feature Construction: The feature construction stage is to construct a new signal feature that can distinguish whether there is a LOS path simply and effectively. Considering the CSI contains rich information of the channel, it is used to extract the signal feature in both time and frequency domain. The mathematical statistical features, including standard deviation, skewness, kurtosis are considered in this paper. Standard deviation reflects the dispersion degree of the samples. Skewness reflects the incompatibility degree of the samples. Kurtosis reflects the sharpness of the sample distribution. These three features are firstly extracted using the received CSI. They have certain differences in environments with and without LOS, but their recognition accuracy is low when they are used alone. In order to make full use of these three features and improve LOS recognition accuracy, a new feature is constructed to complete the LOS recognition in this paper. The new feature is defined as

$$F = A + \frac{e^B}{C}, \tag{1}$$

where F denotes the new feature, A denotes the kurtosis, B denotes the skewness and C denotes the standard deviation.

2) Recognition Algorithm: We use the linear discriminant method to discriminate whether there is a LOS path based on the new constructed feature. The recognition algorithm can be written as follows.

$$g(F) = F + \varepsilon, \tag{2}$$

where ε denotes the threshold. The threshold ε can be calculated using the training samples according to the optimal criterion. When $g(F) > 0$, it is judged that there is a LOS path. On the contrary, when $g(F) \leq 0$, it is judged that there is no LOS path.

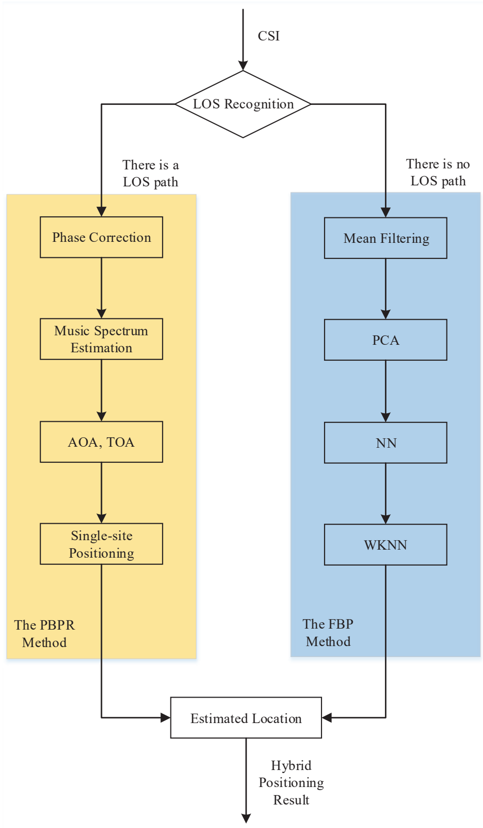

Fig. 1. Single-site hybrid positioning system based on LOS recognition

B. The PBPE Method

When there is the LOS path, the PBPE method is applied for localization. This method estimates the parameters of angle and distance and then calculates the position of the target based on these parameters. The CSI is used to estimate these ranging parameters in this paper. However, due to the interference of ambient noise and hardware limitations during the transmission process, the phase of CSI will shift. Therefore, a phase correction method [11] based on linear transformation is used to preprocess the CSI data to obtain more stable phase information. Furthermore, on the basis that the signal subspace and the noise subspace are orthogonal to each other, the *multiple signal classification algorithm* (MUSIC) is then utilized to estimate these ranging parameters based on the pahse-corrected CSI in this paper.

The principle of the MUSIC algorithm is based on the phase difference between different antennas when the signals arrive at the antenna array. In the multipath environment, the array response of the m-th antenna can be expressed as

$$\Phi\left(\theta_p\right) = e^{-j2\pi \times d \times (m-1) \times f_k \times \sin(\theta_p)/c}, \tag{3}$$

where d denotes the distance between adjacent antennas, m denotes the m-th antenna, f_k denotes the subcarrier frequency of the k-th subcarrier, θ_p denotes the incident angle of the p-th path and c denotes the speed of light.

In addition to the phase difference caused by the antenna spacing, the phase difference is also caused due to the different

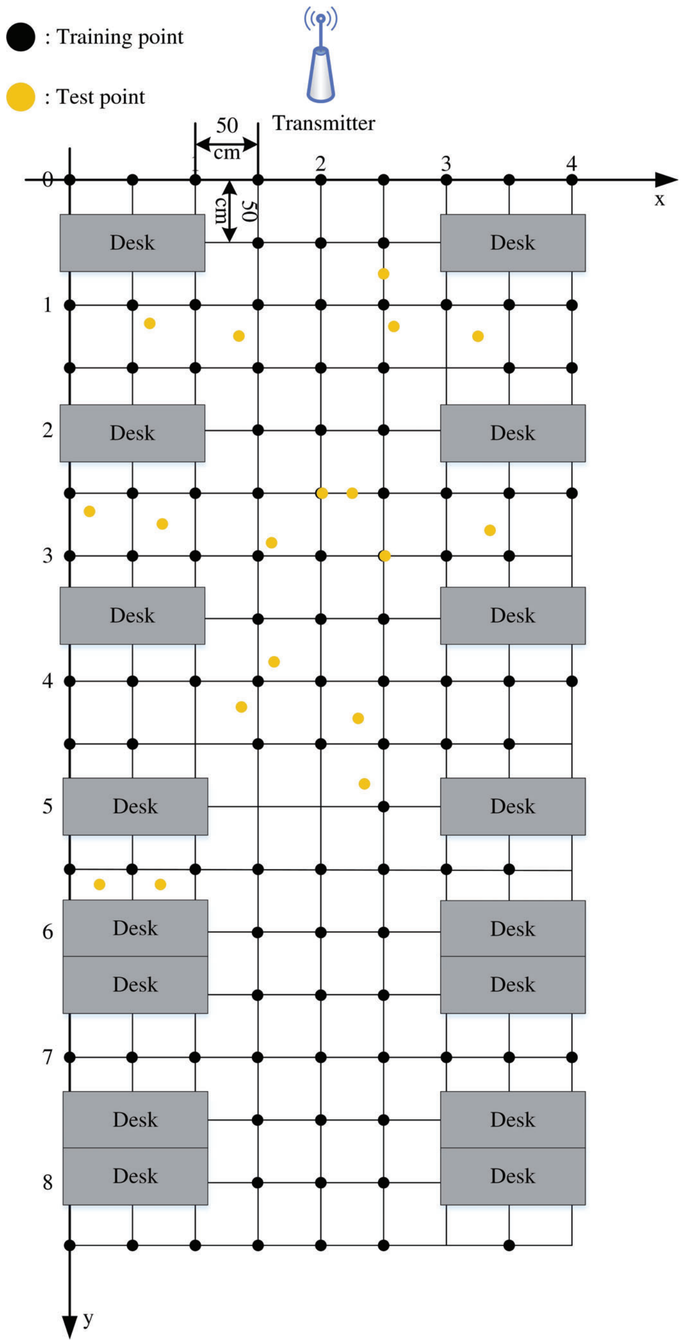

Fig. 2. The floor plan of the laboratory

frequency of each subcarrier. For the p-th path with the arrival time τ_p, the frequency response of the k-th subcarrier can be expressed as

$$\Omega\left(\tau_p\right) = e^{-j2\pi \times f_k \times \tau_p}. \tag{4}$$

The MUSIC spectrum function is constructed through the steering vector and the noise subspace, and the required propagation time and the incident angle are estimated by solving the spectrum function. Based on these parameters, the coordinates of the unknown points can be calculated through geometric relations.

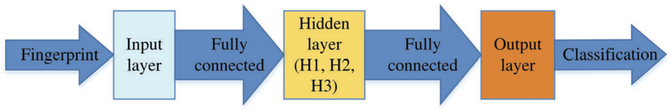

Fig. 3. The structure of neural network model

C. The FBP Method

In order to achieve higher accuracy in areas where there is no LOS path, a FBP method based on NN model is proposed for localization in this paper. The FBP method can be divided into three stages: data preprocessing, offline training, and online positioning.

1) Data Preprocessing: Because the dimension of the received CSI is too large to be the input of NN, it is necessary to preprocess the CSI to reduce the complexity of the positioning system. What's more, considering there is no LOS path, the signals are reflected and scattered and contains a lot of noise, resulting in poor performance of the positioning system. To deal with these problems, the mean filtering method is firstly used to eliminate noise interference. After mean filtering, PCA is applied to do dimensionality reduction on CSI. In the data preprocessing stage, the signal characteristic fingerprint library corresponding to the reference points is finally established.

2) Offline Training: In the offline training stage, a NN model is desighed to establish non-linear relationship between wireless signal characteristics and reference points based on the fingerprint library established in advance. The structure of the NN model is shown in Fig. 3. The NN model contains three hidden layers and the numbers of neurons in the three hidden layers is selected as 1400, 700, and 350 respectively in this paper. In order to fully capture the information contained in the input data, the number of neurons in the first hidden layer is large, and the numbers of neurons in the second and third layers decrease sequentially, thereby constructing a complex deep NN.

3) Online Positioning: In the online positioning stage, the test data set is firstly preprocessed using mean filting and PCA. Then we input the processed data into the trained NN. The NN will match the test data with the fingerprint library and output the numbers of reference points with similar signal characteristics. The reference point whose fingerprint is more similar to that of test point will have a higher weight. In order to comprehensively consider the impact of the reference points near the test point, WKKN is used to calculate the position coordinates. The final estimated position coordinates can be expressed as

$$(x, y) = \sum_{i=1}^{K} w_i \left(x_i, y_i\right), \tag{5}$$

where K denotes the number of reference points that need to be considered, w_i denotes the weight of the i-th reference point in the K outputs, (x_i, y_i) denotes the coordinates of the i-th reference point.

III. RESULT

The experiment is carried out in a 10m×5m laboratory, which is a typical complex indoor scene. The *minimum mean square error* (MMSE) distance is used as the performance index. We have carried out the following experiments to verify the performance of the HP system proposed in this paper.

A. Data Collection

This paper takes the *long term evolution* (LTE) as an example for data collection. The software radio platform ZedBoard is used to obtain the CSI at different locations in this paper. The floor plan of the laboratory is shown in Fig. 2. Taking the complexity of the indoor environment into account, the distance between adjacent reference points is set to 50cm. There are totally 105 reference points. In addition, 18 points are randomly selected as the test points to evaluate the performance of our proposed HP system.

The bandwidth of the LTE system is 10MHz and the subcarrier spacing is $\Delta f = 15$kHz. The center frequency is 2GHz. In the experiment, the 90ms CSI packet is collected at each point and the final extracted CSI at each point is a 600×2×2×1260 tensor, representing 600 subcarriers in the frequency domain, 1260 *orthogonal frequency division multiplexing* (OFDM) symbols in the time domain and 2×2 *multi-input multi-output* (MIMO) in the spatial domain.

B. LOS Recognition

According to the analysis of the training data set, the CSI of the 500-th subcarrier at the first transmitting antenna and the first receiving antenna is used to construct the new feature in the data preprocessing stage. In the experiment, the testing points are classified and evaluated using the LOS recognition algorithm proposed in Part A of Section II. The accuracy rates of using the new feature and other typical statistical features are shown in Table I. It can be clearly seen that the constructed new feature improves the accuracy of LOS recognition greatly. It is reasonable considering that the new feature is a combination of other three features.

TABLE I
ACCURACY OF LOS RECOGNITION WITH DIFFERENT FEATURES

Feature	Accuracy
Standard Deviation	61.11 %
Skewness	72.22 %
Kurtosis	83.33 %
New Feature	88.89 %

C. Performance Comparison Between FBP and PBPE in the Areas With or Without LOS Path

In the experimental environment, there are areas where the LOS path exists and the LOS path does not exist. In order to verify the performance of the PBPE method and the FBP method in different areas, the testing points is divided into two categories according to whether there is the LOS path. The MMSE *cumulative distribution function* (CDF) curve of the PBPE method and the FBP method is shown in Fig. 4.

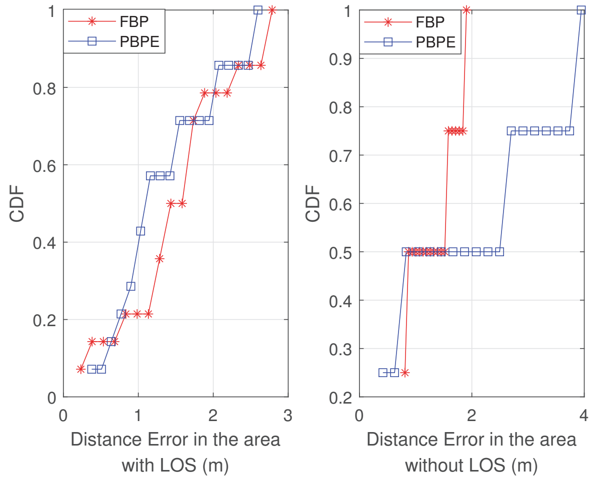

Fig. 4. The performance comparision between the FBP method and the PBPE method in different areas with or without LOS path

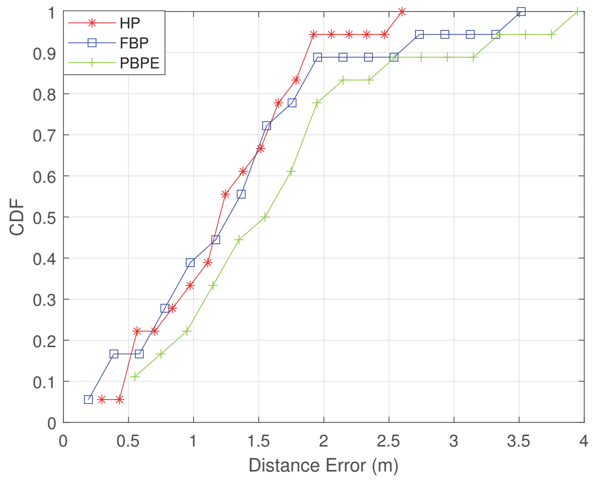

Fig. 5. The performance comparision between HP, FBP and PBPE

As shown in Fig. 4, when there is a LOS path, the PBPE method can estimate the ranging parameters accurately and achieve accurate positioning results. However when there is no LOS path, the estimation error of the ranging parameters will be large, resulting in large positioning error of the PBPE method. Different the PBPE method, the FBP method is less affected by the environment. Therefore, the positioning performance of the FBP method is much better in the areas without the LOS path.

D. Performance Comparision Between HP, FBP and PBPE

In order to verify the advantages of our proposed HP system, we compare it with the system only using the FBP method or the PBPE method. The MMSE CDF curve is shown in Fig. 5.

As shown in Fig. 5, the HP system reduces the maximum estimation error to 2.6m, which greatly improves the stability of the positioning system. While when the FBP method and the PBPE method are used alone, the maximum error reaches 3.15m and 3.94m respectively. The reason for the largest error of the PBPE method is that when there is no LOS path, the signals at the receiving end contain all reflected and scattered

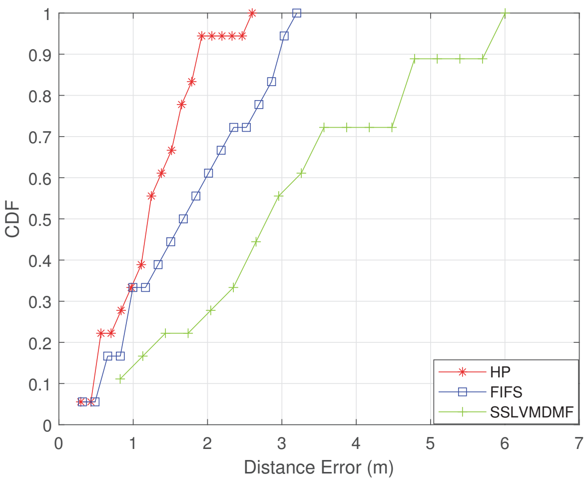

Fig. 6. Performance comparision between the HP system and other existing systems

signals, which makes it impossible to estimate the ranging parameters accurately. The inaccurate ranging parameters lead to poor positioning results. It can be clearly seen that the HP system gives full play to the advantages of the two methods and improves the positioning accuracy.

E. Performance Comparision Between the HP system and other existing systems

The single-site HP system proposed in this paper is also compared with the other two well-known positioning systems. The comparison results are shown in Fig. 6. *Single-site localization via maximum discrimination multipath fingerprinting* (SSLVMDMF) uses the data of all the other locations in the database, and leverages it to extract a fingerprint that is as different as possible from the other fingerprints in the database [12]. *Fine-grained indoor fingerprinting system* (FIFS) is another fingerprint positioning system that explores the PHYlayer CSI and leverages the CSI values including different amplitudes and phases at multiple propagation paths [13].

Furthermore, Table II gives the MMSE distance and median error distance. The experimental results show that the MMSE of the HP system is 1.36m, which is much better than 1.79m of FIFS and 3.14m of SSLVMDMF. Therefore, our proposed HP system can realize single-site localization and can achieve higher positioning accuracy than the other two existing systems.

TABLE II
ERROR COMPARISON BETWEEN DIFFERENT POSITIONING SYSTEMS

Method	MMSE(m)	Median error(m)
FIFS	1.79	1.76
HP	1.36	1.53
SSLVMDMF	3.14	3.41

IV. CONCLUSIONS

A HP system based on LOS recognition is proposed in this paper. It is composed of three parts: LOS recognition, the PBPE method and the FBP method. In the LOS recognition phase, a new feature is constructed to complete LOS recognition easily and effectively. According to the recognition result of whether there is a LOS path in the environment, the HP system adaptively selects the optimal positioning method. Finally our proposed HP system has been compared with other existing positioning systems, and the experimental results show that the HP system can complete single-site localization and can achieve higher positioning accuracy.

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