Optimization Methods of Motion Recognition System Based on CSI

Hongtao Zhu[1], Dezhi Li[1], Zhenyong Wang[1,2(✉)], Qing Guo[1], and Zhenbang Wang[1]

[1] School of Electronics and Information Engineering, Harbin Institute of Technology, Harbin, Heilongjiang, China
zhuhongtao@stu.hit.edu.cn, {lidezhi,ZYWang,QGuo}@hit.edu.cn, zhenbangw@163.com
[2] Shenzhen Academy of Aerospace Technology, Shenzhen, Guangdong, China

Abstract. Motion recognition system based on WiFi overcomes the limitations of the system based on vision and wearable sensor in the past, it's the most ideal design for the implementation of this technology. On the basis of realizing the motion recognition system based on CSI amplitude, a joint optimization algorithm based on CSI amplitude and phase difference is proposed in this paper. Through linear transformation and continuation compensation of CSI phase, the problem that phase distribution error can't be used is overcome. The amplitude of CSI value of received motion signal is obtained. It is combined with the phase difference of multiple antennas at the receiving end as the basis signal. In order to solve the problem of high complexity of the system, an optimization algorithm based on amplitude distribution variance is proposed. The experimental results show that the system can recognize three different motions with high accuracy, and after using the optimization algorithm, the average recognition accuracy of the system is increased by 4.7%, and the distinguishing rate between static and motion behavior is greatly improved, which has a certain universality.

Keywords: Motion recognition · CSI · Phase difference of multiple antennas · Variance of amplitude distribution

1 Introduction

With the rapid progress and popularization of high-speed processing chip, communication technology and network technology, human-computer interaction (HCI) technology [1] plays an important role in all aspects of people's lives. In many applications of human-computer interaction technology, motion recognition, as an important component of smart city and smart home, has attracted wide attention from academia and industry. According to the channels of motion data acquisition, the existing motion recognition systems can be divided into three categories: motion recognition based on wearable sensors, motion recognition based on vision and motion recognition based on WiFi signals. Radio signals have the advantages of strong penetration, wide sensing range, no recording of sensitive information involving privacy, and no need to carry additional devices to measure. More importantly, with the development of communication

M. Jia et al. (Eds.): WiSATS 2019, LNICST 280, pp. 251–264, 2019.
https://doi.org/10.1007/978-3-030-19153-5_26

technology, WiFi infrastructure is everywhere. Therefore, the use of radio signal detection motion is the most ideal form at present. As early as 2013, Nuzzer, a motion research system based on Received Signal Strength (RSS), first appeared in the literature [2]. The system uses Bayesian formula to locate people whose indoor positioning error is less than 2 m, and judges whether there is human movement in the room according to the variance of the received signal. In [3], WiGest motion recognition system is proposed to extract three basic changes from the influence of different gestures on RSS waveforms, namely, rising, falling and pausing. By combining the three changes with the change of RSS amplitude to detect different gestures, the average recognition accuracy is 86%. Document [4] presents a motion recognition system WiSee for indoor environment on USRP. By observing the instantaneous Doppler frequency shift caused by the movement of people, the system can judge the different motion states of human body, and the recognition accuracy of 9 different behaviors is 94% on average. However, given the number of transmit and receive antennas, the system can only realize single user motion recognition with no more than three interference in the environment. Reference [5] presents a representative E-eyes behavior recognition system, which uses WiFi commercial equipment to statistics CSI amplitude distribution information, uniquely identifies walking and in-situ activities, and achieves an average real case rate of over 96% and a false positive case rate of less than 1% in two different environments. However, the system needs to work in a more stable environment, which limits the use of indoor environment where other users or large pets often exercise. [6] The amplitude of CSI from the same access point (AP) is measured simultaneously by multiple receiving devices. Three data fusion methods, namely majority voting fusion, possibility fusion and feature fusion, are used to select communication links with less interference and higher quality to identify different behaviors. Compared with E-eyes, this method identifies the environment in which multiple users coexist simultaneously. The rate increased by 8%.

Through the analysis of previous work, the behavior recognition system based on WiFi signal can distinguish different motion behavior by observing the changes of CSI of WiFi signal. Therefore, this paper improves the motion recognition system from two directions. Firstly, most of the existing systems only extract the amplitude of CSI, which wastes the phase information that CSI can provide. In this paper, a joint basis signal optimization algorithm based on the amplitude and phase difference of CSI is proposed. By comparing the amplitude of the received signal at the receiving end of the system and designing the processing algorithm of phase linear transformation and phase continuation compensation, the solution is given. The influence of singularity on signal recognition accuracy and the application of CSI phase can't be applied. Secondly, the existing motion recognition system directly uses the traditional classification algorithm to distinguish different behaviors. In the process of matching the behavior to be identified and the existing behavior template, it needs to compare the similarity of the behavior one by one, which has high complexity. In this paper, an optimization algorithm based on the variance of the amplitude distribution of subcarriers is proposed. By comparing the variance of the amplitude of CSI signals between adjacent packets with the variance of the distribution of subcarriers, the severity of the motion is defined, and the fast distinction between the motion and the static behavior is realized, which saves the training time of the static behavior data and reduces the overall complexity of the system.

The remainder of the article is structure as follows: in the Sect. 2, and the system model based on CSI motion recognition is introduced. In the Sect. 3, the continuation compensation algorithm and the joint optimization algorithm based on amplitude and phase difference are designed to realize the use of two basic signals. At the same time, the optimization algorithm based on amplitude distribution variance is designed to optimize the system. Section 4 compares the performance of the improved model with the original model, and the optimization results are compared with the results of related literatures. Section 5 concludes the paper.

2 System Architecture Based on CSI Motion Recognition

2.1 CSI

Wireless channel is usually modeled by channel impact response (Channel Impulse Response, CIR) [7]. CIR can be expressed as:

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

Where α_i, θ_i and τ_i represent amplitude attenuation, phase shift and time delay of I path respectively.

Similarly, when converted to frequency domain, multipath propagation can be characterized by channel frequency response (CFR), which includes amplitude-frequency response and phase-frequency response.

Similarly, when converted to frequency domain, multipath propagation can be characterized by channel frequency response (CFR), which includes amplitude-frequency response and phase-frequency response.

Using the wireless network card, a set of CSIs can be obtained from the wireless signal packets received at each time. Each CSI is based on the sub-carrier frequency difference as the frequency sampling interval. The CFR samples on 30 OFDM sub-carriers in the bandwidth can be collected. The CSI corresponding to each sub-carrier is:

$$CSI_k = \frac{1}{K}\sum_{k=1}^{K} \frac{f_k}{f_0} \times \|H_k\|, \quad k \in (-15, 15) \tag{2}$$

Where f_0 is the center frequency and f_k is he frequency of sub carrier K.

2.2 System Architecture

Based on the principle of WiFi signal behavior recognition, this paper designs a complete system structure, which is shown in Fig. 1. The system consists of two parts: hardware module and software module. The left dotted wire frame is mainly composed of the hardware part and the right is mainly composed of the software module. The system is mainly used to identify and distinguish three different behaviors, including one static behavior and two moving behaviors. For convenience, this paper uses motion 1 to express the behavior of repeated movement after entering the environment, motion 2 to express the behavior of leaving immediately after a short stay in the environment, and motion 3 to express the behavior of not entering the environment.

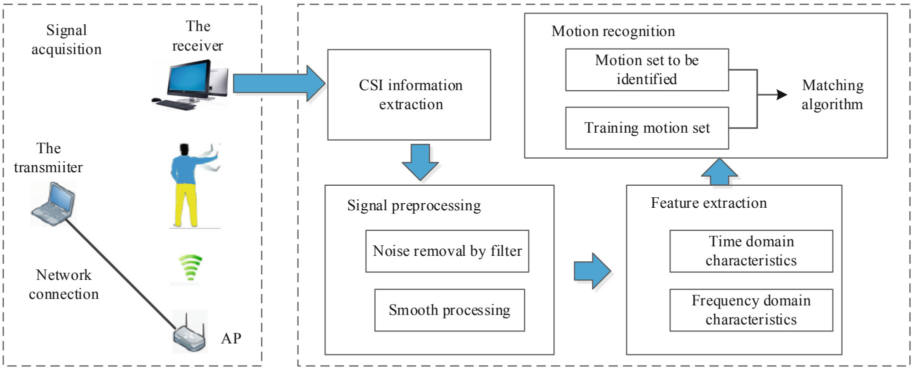

Fig. 1. Structure of motion recognition system based on CSI.

The software module designed in this paper consists of four parts: CSI signal collection, signal pre-processing, feature extraction and motion recognition. After collecting the motion data, the receiver extracts the CSI information. Because the wireless signal is affected by the external environment and various factors within the system, it is necessary to pre-process the data signal, and remove the sudden change data with the help of smoothing algorithm while filtering the noise. The processed signal enters the feature extraction step. In this paper, the features of different wireless signals are extracted in time domain and frequency domain and sent to SVM for training, thus forming the feature data set. Finally, the data set is divided into training set and testing set by cross validation method, and the optimal training template is determined by grid search method. When the test identifies different motions, the motion to be identified is matched with the training motion template to realize the system function.

3 Improved Optimization Algorithms

3.1 Joint Optimization Algorithm Based on Amplitude and Phase Difference

Linear Transformation Processing of Phase. Due to the Clock out of sync and random noise between the receiver and the transmitter, the phase information obtained directly is very random and can't distinguish different behavior. In order to avoid wasting valuable phase information provided by CSI, the existing phase must be corrected. The phase calibration algorithm is introduced to deal with the phase.

Assuming that the phase of the i-th sub carrier of the measured CSI data is A, so the phase can be expressed as follow:

$$\hat{\phi}_i = \phi_i - 2\pi\frac{k_i}{N}\delta + \beta + Z \tag{3}$$

Where ϕ_i is the true phase; δ is the time offset between the receiver and the transmitter, which is the main factor causing the phase error; β is the unknown phase offset; Z is the noise introduced into the measurement process; k_i is the subcarrier index of the subcarrier i; N is the FFT point number.

In order to eliminate the influence of δ and β, two variable a and b are defined.

$$a = \frac{\hat{\phi}_n - \hat{\phi}_1}{k_n - k_1} = \frac{\phi_n - \phi_1}{k_n - k_1} - \frac{2\pi}{N}\delta \tag{4}$$

$$b = \frac{1}{n}\sum_{j=1}^{n}\hat{\phi}_j = \frac{1}{n}\sum_{j=1}^{n}\phi_j - \frac{2\pi\delta}{nN}\sum_{j=1}^{n}k_j + \beta \tag{5}$$

Assume that the frequency of the subcarriers is completely symmetrical. b can be expressed as follows:

$$b = \frac{1}{n}\sum_{j=1}^{n}\hat{\phi}_j = \frac{1}{n}\sum_{j=1}^{n}\phi_j - \frac{2\pi\delta}{nN}\sum_{j=1}^{n}k_j + \beta \tag{6}$$

By subtracting the linear variable $ak_i + b$ from the measured phase, the linear combination of the true phase for removing the random phase offset is obtained. And it is shown as Eq. 7.

$$\tilde{\phi}_i = \hat{\phi}_i - ak_i - b = \phi_i - \frac{\phi_n - \phi_1}{k_n - k_1}k_i - \frac{1}{n}\sum_{j=1}^{n}\phi_j \tag{7}$$

At this time, the error term of random noise is no longer included in the phase signal. The phase obtained by linear calibration is not the real CSI phase, but the linear transformation value of the real phase. Suppose A is frequency independent and identically distributed, then:

$$\sigma^2_{\tilde{\phi}_i} = c_i\sigma^2_{\tilde{\phi}_i}, \quad c_i = 1 + 2\frac{k_i^2}{(k_n - k_1)^2} + \frac{1}{n} \tag{8}$$

This means that the difference between the calibrated phase variance and the true phase variance is only a constant multiple related to frequency. That is to say, the change trend of the calibrated phase signal can be used to reflect the fluctuation of the real phase, which solves the problem that the phase can't be used because of the random distribution of the real phase in theory.

Joint Optimization Algorithm. This paper considers the combination of amplitude and phase of the receiver's multiple antennas as the base signal. The phase difference between the two antennas at the receiving end is used as a new basic signal, which not only utilizes the phase information, but also takes into account the spatial characteristics of the signal. The feasibility of phase difference as a base signal is proved theoretically.

Because amplitude can be used to distinguish different behaviors in the form of curve fluctuation, phase difference can enhance the recognition ability of wireless signals in different directions in different environments and improve the recognition accuracy in complex environments. Therefore, combining amplitude and phase difference, a joint optimization algorithm based on amplitude and phase difference of CSI is proposed to further improve the accuracy of CSI. By comparing the amplitudes of CSI signals received by three antennas at the receiving end, the two items with the largest amplitudes are selected, and the phase difference of the corresponding CSI signals is calculated. If the amplitudes of the received signals of three receiving antennas are identical, two of them are arbitrarily selected to calculate the phase difference; if the amplitudes of the signals of two of the three antennas are equal, the phase difference of the antennas is calculated directly; otherwise, the two antennas corresponding to the two maximal amplitudes of CSI are selected directly. Then the continuation compensation and linear transformation processing of the calculated phase difference are processed.

3.2 Classification Optimization Algorithm Based on Variance of Amplitude Distribution

Distinction Between Motion and Static Behavior. The traditional classification and recognition algorithm only uses SVM to train and test the data feature set. This method takes a long time in the training process, making the whole system more complex. This section designs an optimization algorithm from the state of motion to achieve a quick distinction between different behaviors. Firstly, motion and static behavior are distinguished from the perspective of signal characteristics. The obvious difference between static and motion behavior is that the amplitude of the collected CSI signal fluctuates sharply in the time domain. Obviously, the motion behavior must have more obvious fluctuations. Compared with the static behavior, the variance of the amplitude of the signal is larger. Comparing with the first sub-carrier of the three motions in the non-interference experimental environment, the amplitude of the signal is larger. The amplitude of the CSI signal is shown in the Fig. 2.

Observation of Fig. 2 shows that compared with motion 3, motion 1 and motion 2 have larger amplitude of CSI and more obvious signal fluctuation. Therefore, the variance of signal fluctuation can be used to measure the stability of CSI amplitude distribution. At the same time, the variance of signal distribution considering subcarrier

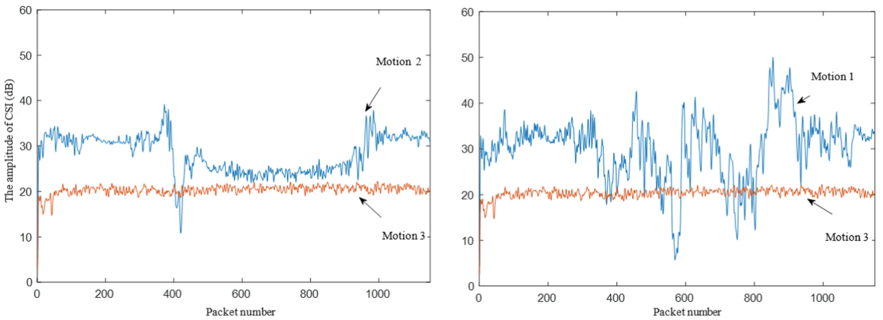

Fig. 2. CSI amplitude of movement and rest behavior changes with time.

variation is used to further distinguish between motion and static behavior. The distribution of the CSI amplitude of the three movements in the frequency domain is compared, and the result is shown in Fig. 3.

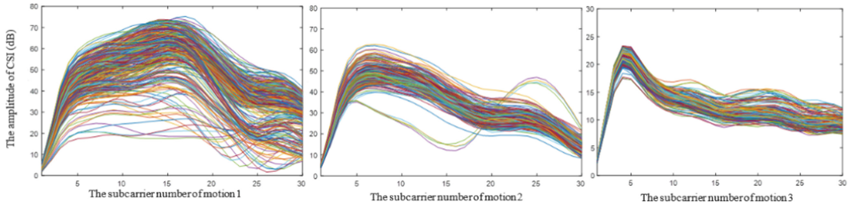

Fig. 3. The CSI amplitude distribution of motion and static behavior varies with sub carrier and time.

Figure 3 shows that the amplitude distribution of CSI in frequency domain is different for different motions. Compared with static motion, the amplitude distribution of motion 1 and motion 2 is more scattered and less stable. Therefore, in the frequency domain, the degree of compactness of the distribution between the curvilinear shapes at different times. That means variance can be used to measure the signal stability. From the point of view of mathematical deduction, a new variable is given: the variance of amplitude distribution, then the variance of CSI amplitude difference of adjacent time signal data is shown as:

$$S_j = \frac{1}{n}\sum_{i=1}^{n}\left[\left(d_i - \overline{d}\right)^2\right] \tag{9}$$

Where d_i is the difference between the amplitude of the current j signal and that of the previous time signal CSI signal on the i-th subcarrier, $\bar{d}$ is the mean of the amplitude difference of the current time signal under all subcarriers, and N represents 30 subcarriers.

Obviously, the smaller S is, the more compact the packet distribution between the time and the previous time is, the more stable the behavior is, and the more static the behavior is; otherwise, the larger S is, the closer the behavior is. The changing trend of CSI signal distribution stability can be obtained by calculating the variance of all the moments.

Classification and Recognition Optimization Algorithm. Figure 4 compares and simulates the distribution of amplitude difference in the whole time domain under three different sub-carriers. It can be found that the variance of amplitude distribution of motion 1 and motion 2 is much larger than that of motion 3. Even the variance distribution of the beginning and the end of motion 3 can be separated from the former. Therefore, the corresponding threshold can be set to distinguish static and dynamic behavior. Now, the optimization algorithm based on the variance of amplitude distribution is no longer necessary to carry out large-scale experimental tests on static behavior. It omits the process of pretreatment, feature extraction and feature set establishment. Theoretically, the algorithm complexity of classification and recognition can be reduced.

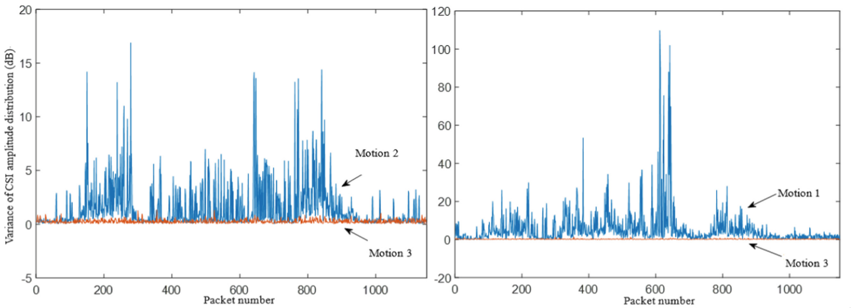

Fig. 4. Comparison results of amplitude distribution variance.

Considering that the optimized system adds a new basic signal of phase difference, in addition to amplitude characteristics, phase characteristics should be introduced in the process of building feature data sets. The eigenvalue of phase difference distribution variance can be used as the eigenvalue of multi-antenna phase difference. The features selected by amplitude can reflect the characteristics of signal distribution. Adding the eigenvalues of the variance of phase difference distribution in time domain can reflect the characteristics of signal more fully, and improve the accuracy of CSI signal acquisition. Compare the variance of phase difference between motion 1 and motion 2, and the result is shown in Fig. 5. The phase difference distribution of different motions is different. Extracting the features can help distinguish different motions. Combining with the amplitude features, it can fully reflect the changes of certain motions and obtain high-precision CSI information recognition.

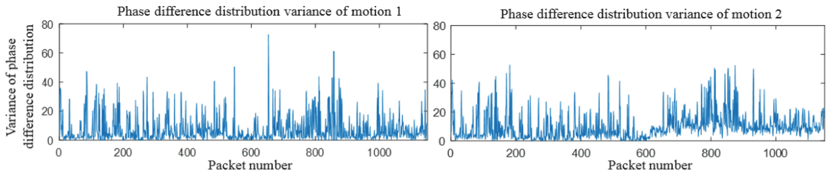

Fig. 5. Comparison of variance of phase distribution of different motions.

4 Experimental Results and Analysis

4.1 System Performance in Strong Interference Environment

In this paper, strong interference environment refers to the experimental environment in which no more than 10 WiFi networks are covered and no more than two unrelated experimenters with small amplitude of motion are involved. The strong interference environment in this paper is shown in Fig. 6.

Fig. 6. Strong interference experimental environment

There are many routers inside and around the environment. There are usually eight WiFi networks covered, and there are not more than two unrelated experimenters in the environment whose mobility is not obvious. Outside the glass door, there are unrelated experimenters who can move freely. Under this environment, the system can move freely. The same frequency interference and multipath interference may be caused.

In order to verify the effectiveness of the optimization algorithm, the optimization algorithm introduced in this paper is used to optimize the system in the strong interference experimental environment. Figure 7 is the confusion matrix obtained from the recognition results of three motions.

Figure 6 shows the accuracy of motion recognition before and after system optimization in strong jamming environment. The experiment shows that in strong jamming environment, compared with the original system before optimization, the recognition accuracy of each motion after optimization has been improved, and the average recognition accuracy has been increased by 4.6%.

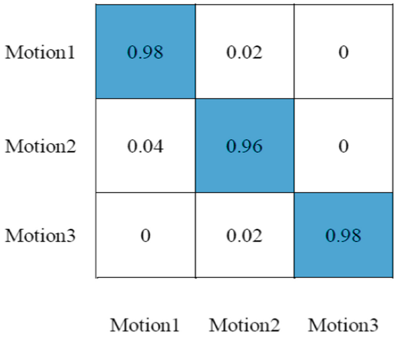

Fig. 7. Confusion matrix of optimization results in strong interference environment

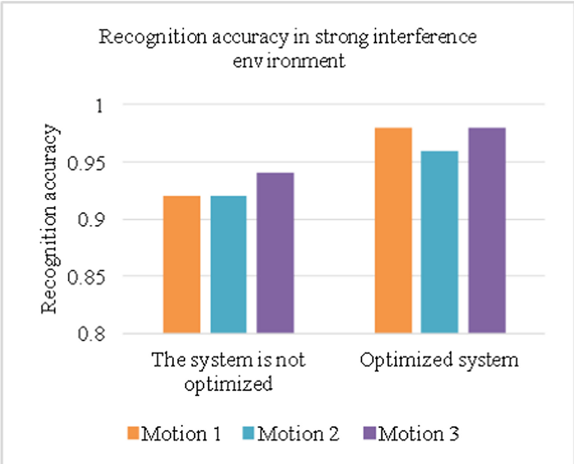

Fig. 8. Accuracy comparison of system identification under strong interference environment.

Figure 7 shows the accuracy of motion recognition before and after system optimization in strong jamming environment. The experiment shows that in strong jamming environment, compared with the original system before optimization, the recognition accuracy of each motion after optimization has been improved, and the average recognition accuracy has been increased by 4.6%.

Table 1 is the time of motion recognition before and after system optimization under strong interference. The comparison shows that the recognition time of motion 1 and motion 2 increases slightly after optimization, which is due to the introduction of the optimization algorithm to complete the distinction between motion and static behavior first, and then to recognize motion 1 and motion 2; but at the same time, the recognition efficiency of motion 3 is significantly improved, the distinction between static behavior. The speed increase is more than half, which has obtained strong system performance.

Table 1. Time of motion recognition under strong interference

	Motion 1	Motion 2	Motion 3
Not optimized	30.04	26.74	10.67
Optimization	31.63	30.63	4.66

4.2 System Performance in Weak Interference Environment

In this paper, the weak interference environment refers to the experimental environment in which no more than five WiFi networks are covered, and there is no unrelated experimenters. The strong interference environment in this paper is shown in Fig. 9.

Fig. 9. Weak interference experimental environment

The number of routers in and around the environment is very small, usually covering two WiFi networks, and there is only one experimenter in the environment for each test. There are no glass doors and other items in the environment, and there is a wall between the external corridor and the environment.

In order to verify the optimization system in weak interference can also realize the function of the system under the experimental environment, using the above optimization algorithm is introduced to optimize the design of system identification, Fig. 10 is a confusion matrix obtained from the recognition results of three actions.

Figure 11 shows the accuracy of motion recognition before and after system optimization in strong jamming environment. The recognition accuracy of the optimized system is 98%, 98% and 100% respectively, and the average recognition accuracy is 98.7%. The highest recognition rate is static motion. Compared with the non-optimized system under the same environment, the average recognition accuracy is improved by 4.7%, which can basically achieve error-free recognition. Compared with the optimization system in strong jamming environment, the average recognition

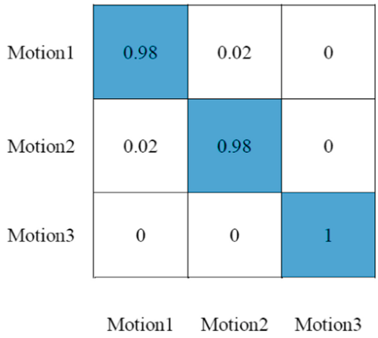

Fig. 10. Confusion matrix of optimization results in weak interference environment

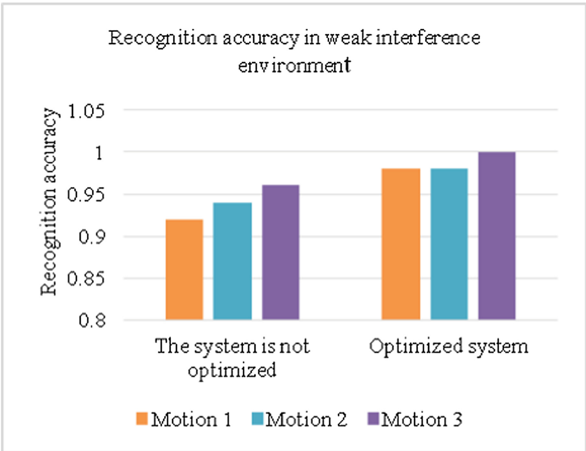

Fig. 11. Accuracy comparison of system identification under weak interference environment.

accuracy in weak jamming environment is improved by 1.4% due to the reduction of obstacles in the environment.

Table 2 is the time of motion recognition before and after system optimization under weak interference. Compared with the recognition time, the recognition time of motion 1 and motion 2 increases slightly due to the introduction of optimization algorithm, and the new system spends a certain amount of complexity to separate motion and static behavior. Therefore, the recognition efficiency of motion 3 is improved significantly, and the recognition time is saved by 56.1% on average and improves the overall performance.

In this paper, the recognition time and accuracy of the optimized system are compared with those of similar systems in reference [6]. The results are shown in Fig. 8. As can be seen from Fig. 12, the system in this paper has a certain advantage in fast recognition of static behavior, but the recognition of dynamic behavior is slightly inferior to that in reference [6]. This is due to the preferential use of optimization

Table 2. Time of motion recognition under weak interference

	Motion 1	Motion 2	Motion 3
Not optimized	24.87	23.16	9.16
Optimization	27.80	26.05	4.02

algorithm to distinguish motion. Although the recognition time of two kinds of motion behavior has slightly increased, the overall performance has been greatly improved. The validity of the fast discrimination algorithm for static and motional behavior is proved.

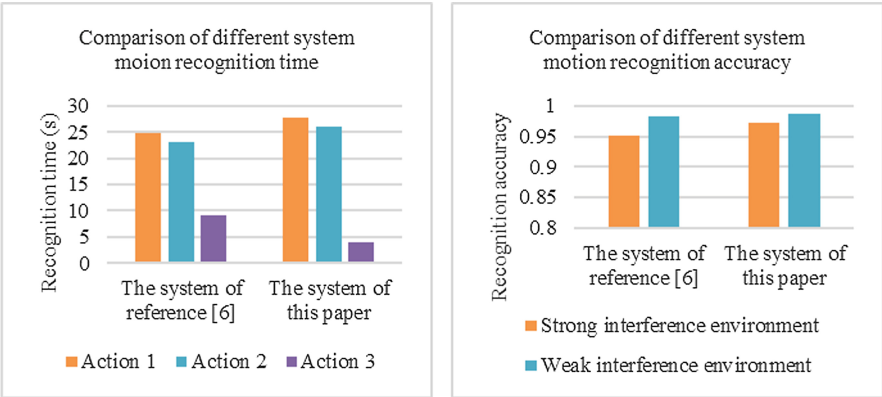

Fig. 12. Comparison of different system motion recognition accuracy.

5 Conclusion

In this paper, we use WIFI signal to design a motion recognition system based on CSI, and propose two optimization algorithms. Two representative experimental scenarios, strong interference environment and weak interference environment, were selected to complete the behavior recognition before and after the system optimization in the two environments, and the recognition accuracy, accuracy and recognition time of the three motions were compared. The experimental results show that the recognition accuracy of the optimized system has been improved to a certain extent, and the recognition accuracy has been improved by 4.6% and 4.7% respectively in strong and weak interference environment. Although the introduction of the optimization algorithm makes the system spend a certain amount of time to establish the phase feature set, making the recognition time of the first two behaviors slightly increased, but compared with motion 3 recognition speed as high as 56.1%. At the same time, the performance of the system is compared with similar systems in reference [6], and the comparative experiments fully prove the robustness of the design system and the effectiveness of the optimization algorithm.

Acknowledgment. This work was supported by National Natural Science Foundation of China (Grant Nos. 61601147, 61571316) and Fundamental Research Funds of Shenzhen Innovation of Science and Technology Committee (Grant No. JCYJ20160331141634788).

References

1. Agarwal, S., Pandey, G.N.: Human computer interaction design for intensive care unit monitors. In: 4th International Conference on Intelligent Human Computer Interaction: Advancing Technology for Humanity, IHCI 2012, pp. 5–8. IEEE Computer Society, Kharagpur (2012)
2. Seifeldin, M., Youssef, M.: A large-scale device-free passive localization system for wireless environments. In: 3rd International Conference on Pervasive Technologies Related to Assistive Environments, PETRA 2010, Pythagorion, Samos, Greece, pp. 1321–1334 (2013). IEEE Transactions on Mobile Computing
3. Abdelnasser, H., Youssef, M., Harras, K.A.: WiGest: a ubiquitous WiFi-based gesture recognition system. In: 34th IEEE Annual Conference on Computer Communications and Networks, IEEE INFOCOM 2015, pp. 1472–1480. Institute of Electrical and Electronics Engineers Inc., Hong Kong (2015)
4. Pu, Q.F., Sidhant, G., Shyamnath, G., et al.: Whole-home gesture recognition using wireless signals. Comput. Commun. Rev. **43**(4), 485–486 (2013)
5. Wang, Y., Liu, J., Chen, Y., et al.: Device-free location-oriented activity identification using fine-grained WiFi signatures. In: 20th ACM Annual International Conference on Mobile Computing and Networking, MobiCom 2014, pp. 617–628. Association for Computing Machinery, Maui (2014)
6. Wang, W., Liu, A.X., Shahzad, M., et al.: Device-free human activity recognition using commercial WiFi devices. IEEE J. Sel. Areas Commun. **35**(5), 1118–1131 (2017)
7. Wang, Y.L., Zhang, Y.Y., Zhu, Y.X.: A novel channel estimation algorithm based on DFT for LTE-a system. In: 2014 International Conference on Electronic Engineering and Information Science, ICEEIS 2014, pp. 59–62. Trans Tech Publications Ltd., Harbin (2014)