WiCLR: A Sign Language Recognition System Framework Based on Wireless Sensing

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Abstract. The non-intrusion and device-free sign language recognition (SLR) is of great significance to improve the quality of life, broaden living space and enhance social service for the deaf and mute. In this paper, we propose a SLR system framework, called WiCLR, for identifying isolated words in Chinese sign language exploring the channel state information (CSI). WiCLR is made up entirely of commercial wireless devices, which does not incur significant deployment and maintenance overhead. In the framework we devise a signal denoising method to remove the environment noise and the internal state transitions in commercial devices. Moreover, we propose the multi-stream anomaly detection algorithm in action segmentation and fusion. Finally, the extreme learning machine (ELM) is utilized to meet the accuracy and real-time requirements. The experiment results show that the recognition accuracy of the approach reaches 94.3% and 91.7% respectively in an empty conference room and a laboratory.

Keywords: CSI · Isolated sign language · Activity recognition · Wireless sensing

1 Introduction

Sign language recognition is a vital application of human-computer interaction (HCI) with social value and technical challenge for deaf and dumb people to communicate with others. The automatic recognition of sign language plays an irreplaceable role in improving the quality of life, expanding living space, and perfecting the service function of public facilities and public institutions. The main data bulletin of the second national disabled sampling survey [1] shows that the number of deaf and dumb people for about 2.66% of the total population in China. However, they have great difficulties in communicating due to the low popularity of standard Chinese sign language and the lack of professional sign language translation. Sign language recognition is used to reduce the communication barriers in deaf and dumb people by detecting, analyzing and explaining sign language actions with computer. In sign language recognition, isolated words are the basis and prerequisite for constructing continuous sentences.

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Sign language recognition methods mainly include sign language recognition based on sensor [2–6] and computer vision [7–9]. Sensor-based systems need wearable device, which this is an intrusion perception that requires the user to carry a specific device (e.g., data glove [2, 3], EMG sensor [4, 5], PPG sensor [6], etc.). Vision-based systems on computer require sufficient lighting and LOS conditions in active environment, which may cause spatial-temporal constraints and privacy issues. With the guarantee of precision, an ideal method of symbolic language recognition is device-independent and privacy-protected.

In recent years, wireless networks have been widely deployed. Wireless signals are not only used for communication, but also can be used to realize environmental sensing by refraction and reflection of the individual in the environment. Especially in the indoor environment, wireless sensing forms a wide spectrum of applications, such as indoor localization [10–14], intrusion detection [15–18], activity recognition [19–24], and so on. At present, received signal strength indicator (RSSI) and channel state information (CSI) are the most common data of wireless sensing in activity recognition. The instability of RSSI greatly restricts the recognition accuracy, but CSI is favored by researchers for its high stability and sensitivity to action. Thus CSI-based approach is a completely new idea for fine-grained micro-movement recognition. E-eyes [19] employs CSI histogram as the fingerprint to identify nine behaviors related to location in daily life. WiHear [20] is exploited to recognize lip language by obtaining the change of CSI with specially-made directional antenna. WiFall [21] uses a feature sequence of CSI to detect falls. Smokey [22] detects the smoking by using the periodicity of CSI influenced by smoking movement. WiFinger [23] utilizes directional antennas to identify ten finger gestures under the 5 GHz. CARM [24] proposes CSI-activity model and CSI-speed model, then uses HMM and feature fusion to identify nine large-scale movements. All these work focus on profiling the influence of the movement of the body on the radio signal propagation, and use the feature template to identify the specific activity. However, the lack of two arms to participate in the identification of the movement, especially the two arms may interfere with each other, greatly increasing the difficulty of identification.

In this paper, we present a sign language isolated word recognition system framework exploiting the channel state information, called WiCLR. Firstly, a signal denoising method using discrete wavelet transform and the principal component analysis is proposed to remove the noise caused by the environment and the internal state transitions in commercial WiFi devices. Moreover, the interpolation method is combined to overcome the sampling defect caused by hardware imperfect and preserve the details of all the subcarriers. Secondly, the multi-stream anomaly detection algorithm is designed to analyze all the CSI streams synthetically in sign language action segment and fusion. Furthermore, the time domain features are extracted to classify different sign language actions. Thirdly, the extreme learning machine (ELM) is utilized as the fine granularity activity classifier via wireless signals for the first time to meet the accuracy and real-time requirements. Finally, CSI data of different sign language actions are collected in both the empty conference room and the laboratory. The experiment results show that the recognition accuracy of WiCLR reaches 94.3% and 91.7% respectively in the two scenarios.

The main contributions are summarized as follows.

(1) A non-invasive and device-free sign language recognition system framework based on physical layer CSI is proposed on COTS wireless devices.
(2) Useful signal denoising method and multi-stream anomaly detection based action segmentation and fusion algorithm are proposed. We analyze all the CSI streams and subcarriers to improve the recognition accuracy and robustness of the system.
(3) ELM is firstly used for wireless sensing-based activity classification and recognition, which greatly improves the recognition efficiency.

2 Preliminaries

2.1 CSI

We can get a set of CSI data by WiFi NICs. The received signal can be expressed as:

$$y = Hx + n \tag{1}$$

where y is the received signal vector, H is the channel gain matrix, x is the transmitted signal vector and n is the noise vector.

Each CSI data represents one of the amplitude and phase of an OFDM subcarrier just as Eq. 2:

$$H(k) = \|H(k)\|e^{j\angle H(k)} \tag{2}$$

where $||H(k)||$ and $\angle H(k)$ are the amplitude and phase of the kth subcarrier respectively.

In Fig. 1, the phase in static environment is evenly distributed in [−π, π]. The irregularity is mainly caused by phase shift. Moreover, the deviation of hardware equipment also brings varieties of errors [24], which requires precise modulation and complex error analysis to eliminate the effect on the phase partly. However, the amplitude information remains relatively stable and has no obvious temporal variability. Therefore, we extract the amplitude information of CSI for further observation.

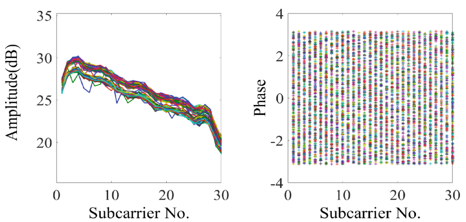


Fig. 1. CSI amplitude and phase in a static environment

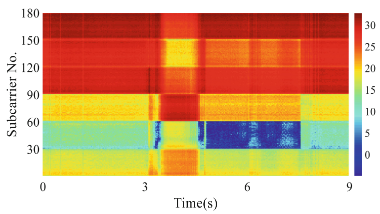
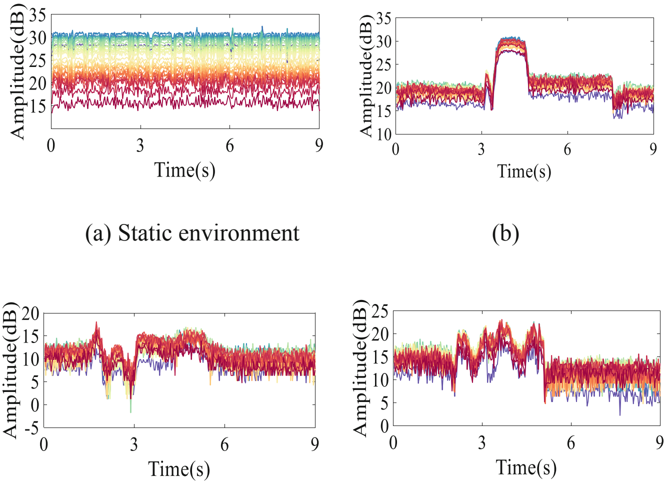


Fig. 3. CSI streams with the same action

The amplitude with the three different sign language activities show in Fig. 2b–d can be identified comparing with that in Fig. 2a in static environment. The amplitude of CSI in dynamic environment fluctuates violently and has quite difference in different actions, since the change of actions causes the continuous change of signal propagation path. The sensitivity of CSI amplitude to dynamic environment is the theoretical foundation for identifying sign languages in this paper. Figure 3 shows the fluctuations of all the subcarriers is correlated. The amplitudes change smoothly across different subcarriers in the same antenna pair and the amplitudes fluctuate violently between different antenna pair. However, they have strong correlation as well, for example, the peak of the CSI stream corresponds to the valleys received by different transceiver antennas.



(a) Static environment (b)

(c)We (d) Bye

Fig. 2. CSI amplitude of static environment and different sign language actions

2.2 MIMO

MIMO is a method for multiplying the capacity of a radio link using multiple transmit and receive antennas to exploit multipath data transmission. Assuming the transmitter has M antennas and the receiver has N antennas, all the data streams can be expressed as below:

$$H = \begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1M} \\ H_{21} & H_{22} & \cdots & H_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ H_{N1} & H_{N2} & \cdots & H_{NM} \end{bmatrix} \tag{3}$$

In the indoor environment, the signal transmission is affected by the multipath effect, thus,the transmission paths of different data streams are different which causes different time delay, amplitude attenuation and phase shift. As a result, the data streams received by different receiving antennas is different.

3 System Design

As shown in Fig. 4, WiCLR consists of four modules: data collection, data preprocessing, action segmentation and extraction and sign language recognition module.

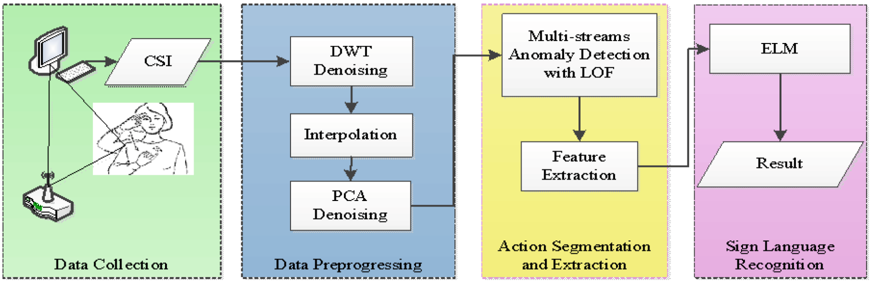


Fig. 4. Overview of WiCLR

3.1 Data Preprocessing

DWT Denoising

The discrete wavelet transform (DWT) has fine time-frequency localization and multi-scale transformation which can process and separate the signal in time and frequency domain simultaneously to get approximate signal and detail signal. Therefore, the denoising effect of discrete wavelet transform is better for non-stationary signals. Comparing with the Butterworth low pass filter and median filter, DWT denoising eliminates the noise effect and preserves the details of the CSI effectively in Fig. 5.

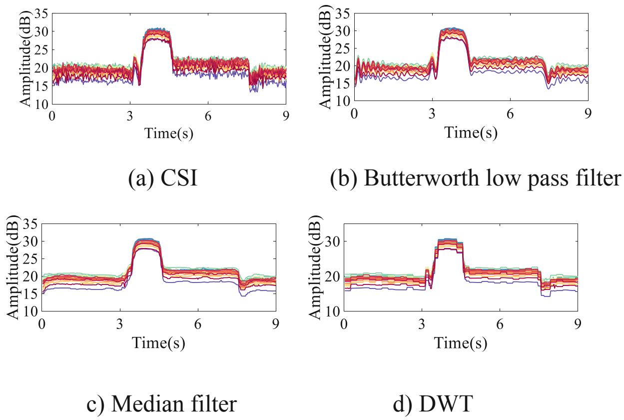


Fig. 5. Different denoising methods

Interpolation

In the transmission of wireless signal, the receiver is affected by data packet loss, transmission delay and other processing delay inevitably. Therefor, even though the transmitter sends packets with a fixed rate, we cannot ensure that the receiver obtains the data packets with the same rate. In other words, the CSI sequence is unevenly sampled. Hence, interpolation is used to get the accurate CSI sequences in time domain. We take advantage of spline interpolation to construct CSI sequences with uniform time intervals by adding approximate values in missing sampling intervals.

PCA Denoising

As shown in Fig. 6, after denoising, the action of sign language has the greatest impact on CSI, the second and third principal component may be the noise caused by the absence of external environment or the internal state of the equipment. Therefore, we choose the first principal component for further analysis. The Fig. 7 shows the CSI sequence after PCA denoising. By preserving the first principal component of the 30 subcarriers, PCA denoising can not only eliminates the uncorrelated noise components that can not be filtered by the wavelet denoising, but also retains the features of the CSI to the maximum to some extent. At the same time, PCA denoising reduces the dimension of CSI and the computational complexity. PCA denoising synthetically calculates the 30 subcarriers without artificially selecting subcarriers, which improves the accuracy of recognition.

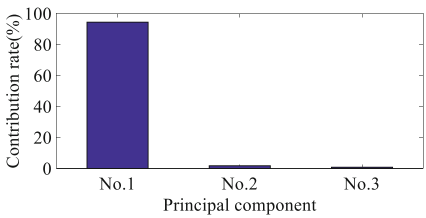


Fig. 6. Contribution rate

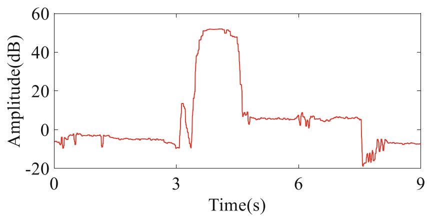
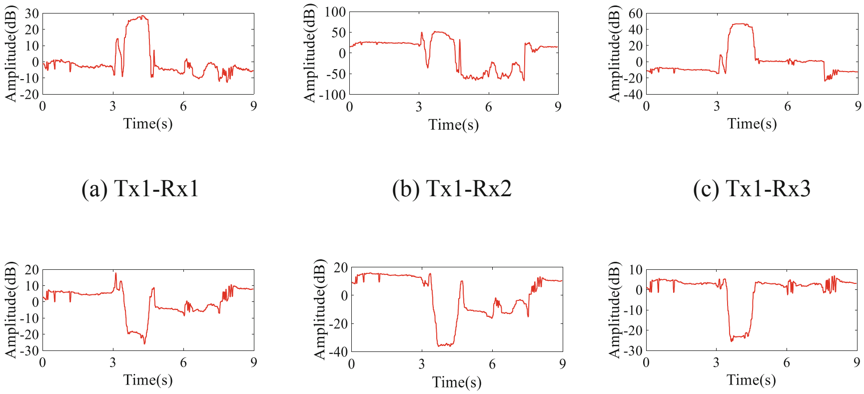


Fig. 7. PCA denoising

3.2 Action Segmentation and Extraction

In MIMO system, there are significant differences in the characteristics of different motions at six CSI data streams. To solve this problem, we propose an action segmentation method based on multi-streams anomaly detection with LOF which analysis of all CSI data streams without the manual selection. The method is more accurate and effective to segment CSI sequences and extract actions. In Fig. 8, the fluctuations of different CSI streams are not the same. The action segmentation as the following signal processing:



(a) Tx1-Rx1 (b) Tx1-Rx2 (c) Tx1-Rx3

(d) Tx2-Rx1 (e) Tx2-Rx2 (f) Tx2-Rx3

Fig. 8. Different CSI streams

The data stream after wavelet denoising, interpolation and PCA denoising is represented as $S_{t.r}$

$$S_{t,r} = \left[\mathrm{S}_{t,r}(1)|\mathrm{S}_{t,r}(2)|\cdots|\mathrm{S}_{t,r}(N)\right]^T \tag{4}$$

(1) Detecting outliers based on LOF for $S_{t,r}(i)$, and get the start point and the end point $t_{begin}(i)$, $t_{end}(i)$ respectively.
(2) Selecting the earliest starting point $\min\left(t_{begin}(i)\right)$ and the last termination point $\max\left(t_{begin}(i)\right)$ as the t_{begin} and t_{end} of the action, and get the CSI sequence $P_{t,r}$:

$$P_{t,r} = S_{t,r}^{t_{end}-t_{begin}} = \left[P_{t,r}(1)|P_{t,r}(2)|\cdots|P_{t,r}(N)\right]^T \tag{5}$$

(3) Calculating the mean absolute deviation (MAD) is as followed:

$$\mathrm{MAD}(i) = \frac{\sum_{t=1}^{k}\left|\mathrm{P}_{t,r}^{t}(i) - m\right|}{k}, i = 1, 2, \cdots, N \tag{6}$$

where m is the average value of sequence $P_{t,r}(i)$. The weight value w_i of the MAD ratio as each piecewise sequence:

$$w_i = \frac{\mathrm{MAD(i)}}{\sum_{i=1}^{N}\mathrm{MAD(i)}}, i = 1, 2, \cdots, N \tag{7}$$

(4) The piecewise sequence H after the fusion is obtained.

$$\mathrm{H} = \sum_{i=1}^{N} w_i P_{t,r}(i), i = 1, 2, \cdots, N \quad (8)$$

Since different CSI data streams have different sensitivity to the same action, we get different start point and end point for different data streams with LOF. It is more accurate and effective to segment the action sequence with the start and end of the fluctuation at the earliest and the last. The average absolute deviation depicts the discrete degree of data, and determines the weights of different data streams with MAD which can not only retain the information of each data stream, but also select the most sensitive data flow characteristics. The Fig. 9 shows the CSI with action segmentation method based on multi-streams anomaly detection with LOF.

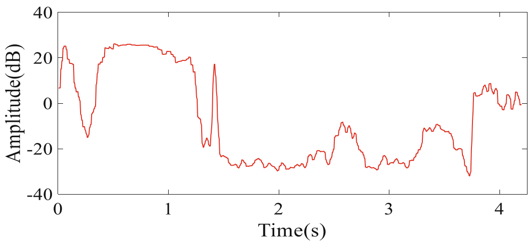


Fig. 9. Multi-streams anomaly detection with LOF

The action segmentation method can segment sign language actions in time domain. However, it can not recognize the category of sign language. At the same time, the detected CSI streams can not be identified by the classifier directly. In order to distinguish the different sign language movements, it is necessary to extract the sensitive action features of the CSI streams. We decide to choose the maximum value, minimum value, mean value, standard deviation, absolute middle difference, four division distances, action duration and signal change rate to reflect the features of CSI completely and effectively.

3.3 Sign Language Recognition

The extracted CSI features are sent to the ELM classifier for recognition. As shown in Fig. 10, the feature sequences of the signed sign language are used as the input of the classifier, and the model is trained by ELM. The number of ELM hidden nodes is adjusted at the test stage until the recognition rate is optimal. Finally, the optimized classification model is used to obtain the recognition results of the test sign language actions.

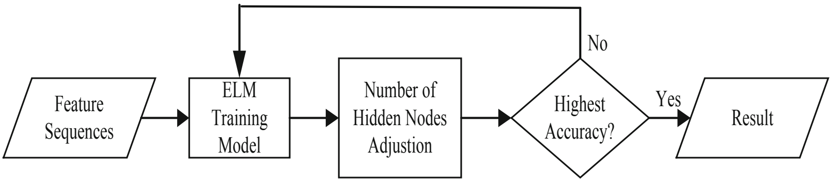


Fig. 10. ELM classification

(1) Data normalization: In this step, we normalize the extracted 8 time domain features between [−1, 1], then put the processed feature sequence and its corresponding label into the ELM classifier as the input.
(2) Training model initialization: we select an appropriate activation function and set up a small positive integer artificially as the number of nodes in the hidden layer to obtain an initial training model. The activation function of ELM classifier can be any infinitely differentiable function. In the laboratory environment, we set the number of hidden layer nodes as 500 and compare four different activation functions as shown in Table 1: Sigmoid, Sine, Hardlim and Trigonometric function, as a result we choose Sigmoid function for its highest recognition accuracy and less volatile (due to the weight a_i and threshold b_i are determined randomly in the classification, the accuracy is volatile).

Table 1. Performance of different activation functions

Function	Testing accuracy	Recognition accuracy
Sigmoid	82.0%	78.2%
Sine	100%	62.5%
Hardlim	69.4%	64.6%
Trigonometric	55.2%	45.8%

(3) ELM classifier optimization: The recognition accuracy of the initial training model is not enough because the number of hidden layer nodes is less and the network structure is simple. In this paper, we optimize the ELM classifier to achieve the best recognition accuracy by increasing the number of hidden layer nodes. In initial, we set the number of hidden layer nodes $L_0 = 10$, then add δ nodes randomly, the total number of nodes $L_k = L_{k-1} + \delta$. Calculating the recognition accuracy test_Acc$_k$, if $0 <$ test_Acc$_k$ − test_Acc$_{k-1} < 1\%$, then increase the step length; if test_Acc$_k$ − test_Acc$_{k-1} < 0$, then reduce the step length, we will recalculate test_Acc$_k$ until the recognition accuracy reaches the best and select L_{k-1} as the number of hidden layer nodes. As Fig. 11 shown, this paper sets the number of hidden layer nodes 1500 to get the best accuracy since the continued increase will cause overfitting and the performance decreases.

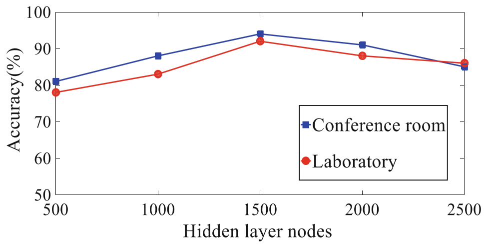


Fig. 11. Effects in different counts of hidden layer nodes

(4) Recognition results: Put the test data set into the optimized ELM classifier and the corresponding expected output as T, the recognition result is shown in following formula:

$$\text{Label} = \arg \max_{1 \leq i \leq m} (Ti) \tag{9}$$

4 Experimental Results

Although sign language has different forms in different countries and regions, these sign gestures are mainly performed with arms, palms and fingers. In our evaluation, we select the standard Chinese sign language isolated words as an object of recognition.

4.1 Experimental Setup

The CISCO WRVS4400N wireless router with 2 antennas is used as the transmitter, and the Intel 5300 NICs with 3 antennas is used as the receiver, and the data processing is analyzed with open source CSI Tools and MATLAB. As shown in Fig. 12, the experimental environment is conference room (3.6 m × 6.6 m) and laboratory (7.4 m × 8.2 m). The identified object sits in the middle of the transceiver terminal, and the receiver is 50 cm away from the transmitter. The height of gesture is as the same as the antennas.

We have 5 volunteers for a week of experimental data collection. They are 3 boys and 2 girls which in 21–28 years old, the weight in 48–82 kg, and the height of 160–180 cm.

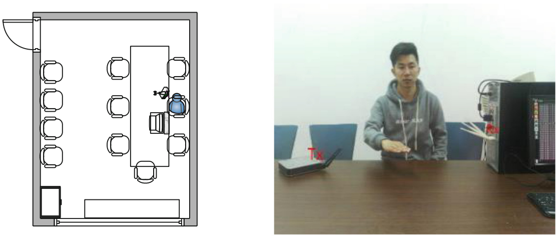
4.2 Performance Metrics

To test the performance of the WiCLR method, we focus on the following indicators:

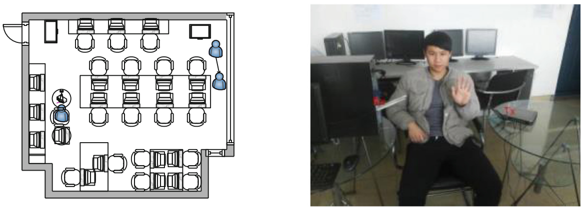
Confusion Matrix: Each column represents sign language actions classified by the system, and each line represents sign language actions made by the test subjects. If $D_{i,j}$

is used to represent cells in column J of column I, then the sign language on behalf of line I $P_{i,j}$ is identified as the probability of sign language in J.

Precision: $P_i = \frac{N^i_{TP}}{N^i_{TP} + N^i_{FP}}$, N^i_{TP} is to correctly identify the number of I, N^i_{TP} is for all the other actions that are mistakenly identified as sign language I, the precision rate indicates the accuracy rate of sign language I.



(a) Conference room



(b) Lab

Fig. 12. Experimental environments

Recall: $R_i = \frac{N^i_{TP}}{N^i_{TP} + N^i_{FN}}$, N^i_{FN} is the number of sign language I is mistaken for other actions. Recall rate indicates the recall rate of sign language I.F1.

F1-Score: $F^i_1 = 2 \times \frac{P_i \times R_i}{P_i + R_i}$, which is the correlation between accuracy and recall is expressed. From 0 to 1, the recognition performance is getting better and better.

Accuracy: $A = \frac{\#Correct}{\#Sum}$, #Correct is the number of the correct signal language, #Sum is the summary of the samples.

4.3 Experimental Analysis

Accuracy of Anomaly Detection

In order to measure the accuracy of the segmentation, the following conditions are considered to be incorrectly segmented: Firstly, the static environment is detected as an exception. Secondly, the action is not detected as an exception. Thirdly, a movement is split into multiple actions; and fourthly, the error of the action endpoint is above 0.5 s. As Fig. 13 shown, the accuracy rate of WiCLR is basically over 90%, while the anomaly detection of single stream is very unstable, and the accuracy rate of different sign language movements is different. The joint multi-streams can improve the accuracy of action segmentation and the performance of sign language recognition.

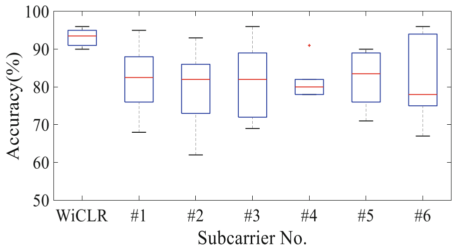
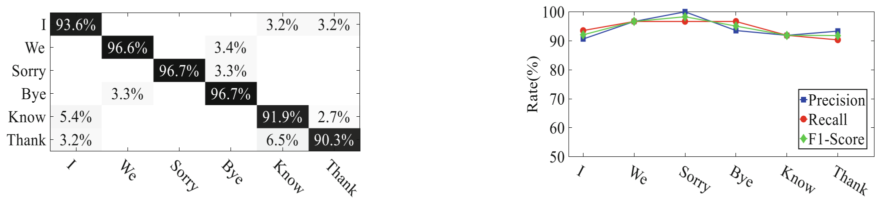


Fig. 13. Segmentation Accuracy

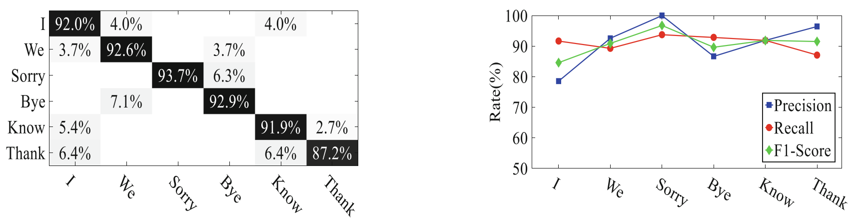
Recognition Accuracy of Sign Language Isolated Words

We test the accuracy of our system in the two typical indoor environments of laboratory and conference room respectively. The experimental results are shown in Fig. 14. In the conference room, the average recognition accuracy of 6 sign language actions is 94.3%, and in the laboratory is 91.7%. In this part, the recognition accuracy of large-scale sign language actions we, sorry and goodbye are better because of the large amplitudes and long durations of signal changing. However the accuracy of micro-scale actions I, know and thank has decreased. The accuracy rate, recall rate and F1 score of each sign language are above 80%, where the action I has the lowest accuracy. Because the action is not only small in action, and the duration is close to thank and know, and the action style or the subaction of we is easy to confused.

In the laboratory, radio signal attenuation is obvious because of many obstacles and rich multipath which cause signals are reflected, refracted and diffracted to the receiver. Thus, the recognition performance is not as good as that in the conference room. However, the recognition accuracy of sign language in the rich or sparse multipath indoor environment is more than 90%. It is proved that our system can be used to extract the feature information of CSI by COTS wireless devices to research the fine grained sign language recognition, and it has certain robustness.



(a) Conference room



(b) Lab

Fig. 14. WiCLR recognition performance

Effects of Different System Classifications

Our classification method is compared with the methods of WiFall [21] and WiFinger [23]. The results of recognition performance of the three methods just as shown in Fig. 15, using ELM to classify sign language will not only have higher recognition accuracy, simple method and less recognition time, but also have a more significant advantage in recognition performance when the sign language is increased.

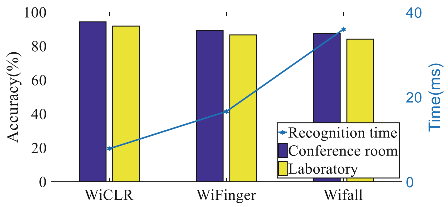


Fig. 15. Different system classifications

Effects of Different Features

In this experiment, we extract one feature: action duration, two features: maximum and minimum, four features: maximum, minimum, standard deviation, duration and all characteristics to compare. As shown in Fig. 16, the accuracy of extracting all of the 8 features is the highest. This is because each feature can only describe a part of the CSI sequence. Only by taking into account all the features can we fully describe the effects of different sign language actions on the wireless signal.

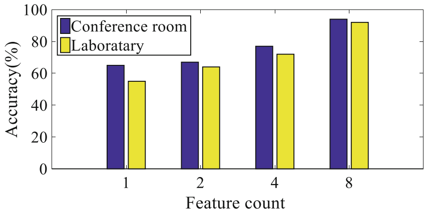


Fig. 16. Different features

Effects of Different Volunteers

For each volunteer, the accuracy rate of sign language recognition in the conference room and the laboratory is calculated respectively. From Fig. 17, the accuracy of the sign language recognition of different volunteers is different. The different habits and proficiency of the sign language action are the main factors that affect the accuracy, and non-standard sign language affects the accuracy of sign language recognition as well.

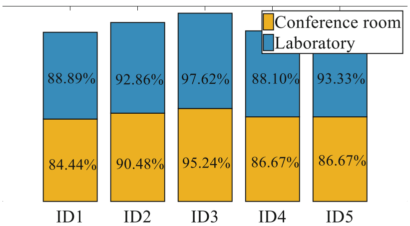


Fig. 17. Different volunteers

5 Conclusion

In this paper, we propose a low-cost, free-device and high precision system to recognize Chinese isolated sign language with the amplitude information of CSI. Firstly, we choose combined denoising method based on DWT, interpolation algorithm and PCA to preprocess the CSI amplitude information which remove the high frequency noise effectively and preserve the effect of the sign language action on the amplitude of all CSI streams to the maximum extent. Secondly, action segmentation method based on multi-streams anomaly detection with LOF is proposed to determine the start and end points of the sign language action. The CSI streams are fused with the weight value and 8 time domain features are extracted. Finally, ELM is used as classifier which is more accurate and faster than other classification methods In the future, our research will combine the phase of CSI and the existing amplitude features to improve the recognition accuracy and the scope of the isolation of isolated words. The hidden Markov model and neural network will also be researched to recognize the continued sentences on the basis of recognition the isolated words of the sign language.

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