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# Recognition of Finger Motions Based on Surface Electromyographic Signals and Artificial Neural Network

Xuelian Yu, Jinwu Qian, Zhen Zhang, Yitian Wu and Zheng Zhang
*School of Mechatronic Engineering and Automation*
*Shanghai University*
*99 Shangda Rd., Baoshan District, Shanghai, China*
{yuxuelian, jwqian, zhangzhen_ta, wytyw&delta2000}@shu.edu.cn

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***Abstract -*** Surface electromyographic (sEMG) signals can be used in medicine, rehabilitation, robotics and industrial fields. This paper proposes a recognition method of finger motions for dexterous control of prosthetic hands. In this work, we record the corresponding sEMG signals from five subjects, and then set up the model by data preprocessing, feature extraction and classification. The results show that high recognition accuracy can be achieved by using time domain feature extraction and artificial neural network. It means that finger motions can be decoded accurately. To acquire the trade-off between the number of channels and the recognition accuracy, we apply channel number reduction and it is found that the number of channels is at least 7 with recognition accuracy of 90.52%.

***Index Terms*** - surface electromyogram, pattern recognition, artificial neural network

## I. INTRODUCTION

In recent years, the research of electromyographic prosthetic hand has been a hotspot in the field of robotics and human-computer interaction. According to the National Center for Health Statistics [1], there are about 2 million amputees in the United States with an increasing of 185,000 new amputees every year. Among these amputations, wrist and hand amputations accounted for 10% of the upper limb amputations, while radial artery amputations accounted for 60% of the total wrist and hand amputations [2]. Because the surface electromyographics (sEMG) signals can reflect the intention of movement before the actual action occurs [3], the electromyographic prosthetic hand can help amputees to complete some tasks in daily life to improve their quality of life.

Nowadays, the decoding of sEMG signals generated by hand movements has achieved good results. Kawano et al. [4] used support vector machine (SVM) to recognize 6 gestures. Feng et al. [5] analyzed the sEMG signals from three channels to classify 6 hand movements with discrete wavelet transform and wavelet neural network, and the classification accuracy can reach 94.6%. Cristhian et al. [6] applied artificial neural network (ANN) to the sEMG signals of 5 gestures collected by Myo Armband in real time and achieved the accuracy of 90.7%. Benalcázar et al. [7] used $k$ nearest neighbour algorithm (kNN) to recognize hand motions and achieved the accuracy of 86%. Geng et al. [8] used convolutional neural network (CNN) to recognize multiple gestures and achieved good results.

The above researches mainly focus on the recognition of hand gestures. The dexterous control of prosthetic hand also requires the recognition of the movement of a single finger. The control of finger motions is more challenging than the control of gesture motions. Firstly, the amplitude of the sEMG signals of finger motions is usually smaller than that of hand motions. Secondly, the muscles controlling finger movements are located in the middle and deep layers of the forearm [9]. Therefore, it is necessary to use several electrodes to provide sufficient information to eliminate ambiguities in anticipated motion.

Previous studies have attempted to recognize finger movements controlled by dexterous hand prostheses. Jiang et al. [10] classified 6 finger movements using four sEMG channels with wavelet transform characteristics. Tenore et al. [11] decoded 12 finger movements of 5 healthy subjects using 32 sEMG channels. For an amputee, 19 sEMG channels were used, and only one time-domain (TD) feature was extracted from each channel. Multilayer perceptron (MLP) was used for classification. Kanitz et al. [12] recognized 12 finger movements using TD features derived from 16 unipolar electrodes with genetic algorithm optimizer and SVM classifier. Fu et al. [13] used the time domain autoregressive (TD-AR) model to process the 6-channel original sEMG data, and used the principal component analysis (PCA) and the probabilistic neural network (PNN) model as the classifier. Castro et al. [14] detected five channels of sEMG signals to recognize six finger movements, and achieved 97% accuracy. Anam et al. [15] proposed a new extreme learning machine and a new dimension reduction method called spectral regression extreme learning machine (SRELM) for finger motion recognition. Five to eight finger movements were recognized by two-channel sEMG signals.

In the above studies, some of them improve recognition performance by increasing the number of sEMG channels, while small number of channels can only recognize a small number of motions. However, due to the limited forearm surface area of amputees, it is unrealistic to improve recognition performance by increasing the number of channels. In addition, increasing the number of channels will also

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increase the complexity, weight and cost of prosthetic hand [16]. To be clinically relevant, the ideal prosthetic hand control should be based on the least number of channels and the least computational complexity to achieve the best recognition accuracy [17]. Therefore, the research in this paper is to improve the accuracy of recognition by carefully selecting the location of electrodes, extracting more TD features and comparing three pattern recognition schemes including SVM, kNN and ANN. Meanwhile, to avoid the information redundancy generated by multi-channels, we apply the channel number reduction to the trade-off between the number of sEMG channels and the recognition accuracy.

The structure of this paper is as follows. The first part describes the research background and the related work of using sEMG to recognize finger movements, and introduces the problems to be solved in this paper. Section II describes the acquisition of sEMG signals and the corresponding signal processing methods. Section III shows the experimental results. Section IV compares and analyses the results of the two experiments, and considers the limitations of the research and the future work. The last part is the summary of this study.

## II. MATERIALS AND METHODS

### *A. Data acquisition*

*(a) Subjects*

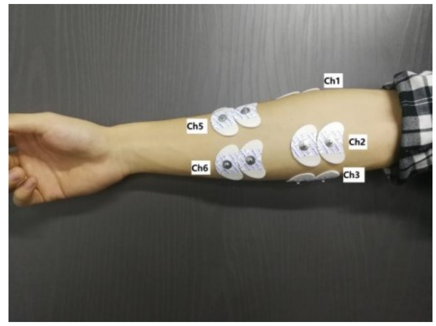
This experiment recorded the sEMG signals of the right forearm of 5 subjects, including 4 males and 1 female, aged from 24 to 26 years.

*(b) Electrode placement and numbers*

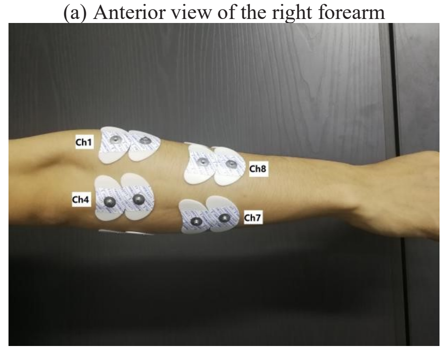
The muscles of human forearm are mainly divided into flexor and extensor. The anterior muscles composed of flexor are mainly located in the medial part of the forearm and are responsible for wrist, elbow and finger flexion. The extensor located in the lateral forearm is responsible for wrist and finger extension. Because most of the muscles responsible for finger movements are deep muscles of forearm, acquisition of finger motion signals is more difficult than acquisition of gesture motion signals. In this paper, 8 sEMG channels with the paired self-adhesive Ag-AgCl electrodes are placed around the forearm. The distance between the electrodes is 24 mm. The bipolar electrodes can minimize crosstalk. Fig. 1 depicts the location of the eight sEMG channels of the subjects. Before placing the electrodes, wipe the forearm skin with alcohol to reduce skin effects, such as impedance, surface grease and dead cell layer.

*(c) Data acquisition instrument*

In this study, the sEMG acquisition equipment is mini-DTS sEMG acquisition instrument with sampling frequency of 1500 Hz from Noraxon (Noraxon, USA). The collected signals can be real-time displayed on the display device through wireless transmission, which is conducive to the observation of the collected sEMG signals during the experiment. The whole acquisition system is shown in Fig. 2.




(a) Anterior view of the right forearm




(b) Posterior view of the right forearm

Fig. 1 Electrode location.

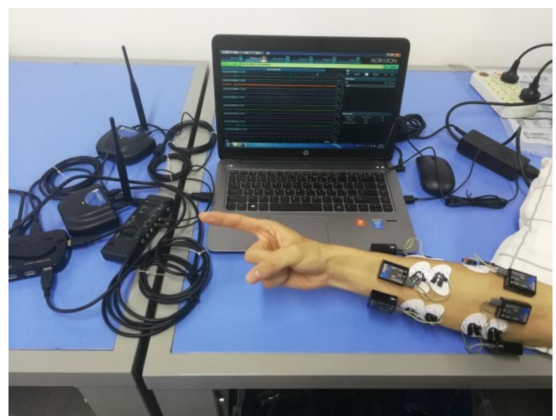


Fig. 2 Signal acquisition instrument.

*(d) Experimental protocol*

Subjects were not trained for sEMG recording before the study and were told to perform 11 classes of finger movements respectively. The 11 classes of finger movements are: thumb abduction, thumb extension, index finger extension, middle finger extension, ring finger extension, little finger extension, thumb flexion, index finger flexion, middle finger flexion, ring finger flexion and little finger flexion. Although the thumb itself can perform four movements, the muscles responsible for thumb adduction are located in the hand itself [9] and cannot be decoded from the upper forearm, so only three thumb movements are included in the recognition. The 11 classes of finger motions are shown in Fig.3. The numbers below the figures represent the labels of each gesture.

During the experiment, each subject sat in a chair in front of the computer to view all sEMG channels signals in real time while performing the actions. The subjects' arms were fixed on the pillow, and a series of finger movements were produced with moderate, constant force. Each finger motion was held on for 3 seconds at a time, and rest for 5 seconds after each completion to avoid muscle fatigue. There are 36 times for each action. Twenty-four of them were used as training data set and twelve were used as testing data set.

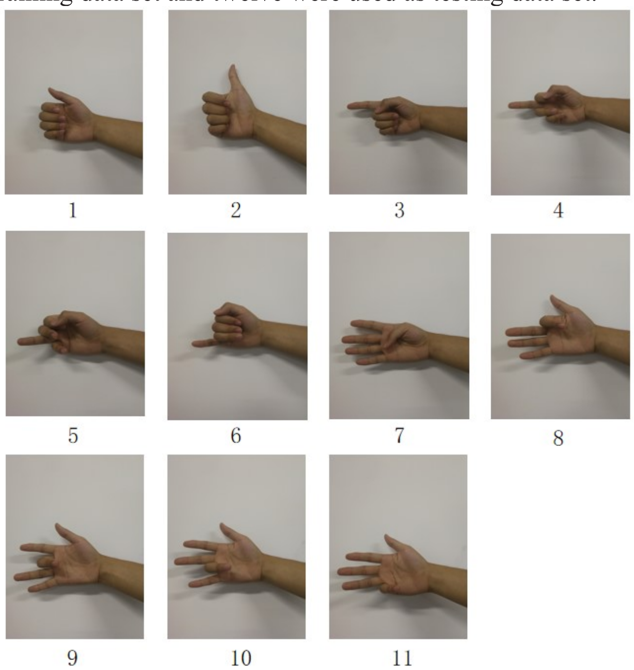



Fig. 3 11 classes of finger movements and corresponding labels

### B. Data processing

*(a) Comparison of recognition performance and selection of the optimal recognition performance*

In this study, MATLAB 2018a (Mathworks, Natick, MA, USA) software is used for data processing. In order to find a better recognition method to evaluate the recognition performance, this paper compares kNN, SVM and BP neural network.

sEMG signal is a kind of non-stationary micro-electric signal, whose amplitude is 0-1.5 mV, useful signal frequency ranges from 0 to 500 Hz, and the main energy is concentrated in 50-150 Hz [18]. Although it has undergone a series of processing such as hardware filtering and denoising, there are still interference such as power frequency noise, peak amplitude and so on, so it is necessary to filter the original signal by software. In this study, fourth-order Butterworth band-pass filter is used, whose band-pass frequency ranges from 20 Hz to 450 Hz. In addition, after frequency transformation of the original signal, it is found that the power frequency noise interference of 50 Hz is large. Therefore, 50 Hz digital notch filter is used to filter power frequency noise interference [19].

sEMG signals are generated 300 ms ahead of limb movements. In order to realize the real-time control of prosthetic hand, the window length needs to be less than 300 ms [5]. Meanwhile, to ensure the continuity of features, time windows and incremental windows are usually used to extract features. In this study, all recorded sEMG data are divided into overlapping windows with length of 200 ms, and the increment between windows is 50 ms.

Generally, the sEMG signal pattern recognition system mainly includes two parts: feature extraction and classification. Time domain feature, frequency domain feature and time-frequency domain feature are the three main feature extraction methods. Because the sEMG signal is recorded in the time domain, the time domain feature extraction is simple and the calculation time is short, which is conducive to the realization of real-time control, so the time domain feature is one of the commonly used methods to extract signal features [20]. In this study, time domain features are used for feature extraction including root mean square value (RMS), waveform length (WL), number of zero crossings (ZC), mean absolute value (MAV) and slope sign changes (SSC). Therefore, each channel can extract five features. We will introduce the five features.

RMS is a characteristic associated with the frequency and amplitude of the sEMG signals. It is actually the valid value of a set of data. It reflects muscle activity. The mathematical expression of RMS is as follows: where $N$ represents the number of sample points in the window and $f_k$ is the data point in the channel.

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} f_k^2} \tag{1}$$

ZC represents the number of times the signal passes through zero in a certain time. It can be used to observe the frequency of signal changes and display the number of signal symbols. Its mathematical expression is as follows: where $\alpha$ represents threshold.

$$ZC = \sum_{k=1}^{N-1} sng(f_k \cdot f_{k+1}) \cap |f_k - f_{k+1}| \geq \alpha \tag{2}$$

$$sng(x) = \begin{cases} 1 & \text{if } x \geq 1 \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

WL is a characteristic reflecting amplitude. It is the cumulative length of waveform over time. It is related to the amplitude, frequency and time of waveform. Its mathematical expression is as follows:

$$WL = \sum_{k=1}^{N} |f_{k+1} - f_k| \tag{4}$$

SSC can reflect the number of changes between positive and negative slopes. The mathematical expression of this characteristic is as follows:

$$SSC = \sum_{k=2}^{N-1} |(f_k - f_{k-1})(f_k - f_{k+1})| \tag{5}$$

MAV reflects the characteristics of the amplitude, which is equal to the average absolute value of the sEMG amplitude of $N$ samples in the sliding window. The mathematical expressions are as follows:

$$MAV = \frac{1}{N}\sum_{k=1}^{N} |f_k| \tag{6}$$

In addition to feature extraction, appropriate classifiers are also crucial to the accuracy of recognition. Researchers have studied a series of classification methods, including neural network [4], SVM [5], fuzzy method [21], random forest [22] and kNN [7]. The principle of kNN is to compare each feature in the test data with the feature in the sample set, and extract the classification label of the data with the most similar feature in the sample set. kNN does not need parameter estimation and training, and is suitable for multi-classification problems [7]. The main idea of SVM is to find a hyperplane in space that can divide all data samples, and make the distance from all data in the sample set to this hyperplane shortest. It is one of the commonly used methods in classification problems. Because sEMG signal has the characteristics of non-linearity and randomization, the classifier with non-linear model can improve the accuracy of classification. As a model of non-linear statistical data, neural network also plays a very important role in sEMG classification [6]. Considering the advantages of these classifiers in previous studies, this paper mainly compares the effects of kNN, SVM and ANN.

*(b) The influence of the number of channels on the classification performance*

In this experiment, we use the best recognition scheme identified in the first experiment. Then, we determine the impact of channel number on recognition performance by using channel number reduction. The goal is to find the smallest number of sEMG channels that can achieve similar performance with all available channels. This enables us to find the best trade-off between recognition accuracy and channel number. Direct exhaustive search algorithm [16][23] is not used to determine the channel number of sEMG channels in this paper, because it has a very high computational load. Its calculation needs to investigate all possible channel combinations to reduce the number of channels. On the contrary, the channel elimination algorithm used in [24] is less computationally intensive than the simple exhaustive search algorithm, because it has the advantage of one-time recursive deletion of the worst-performing channels. During each iteration, the recognition accuracy is calculated and the channel that contributes the least to the recognition performance is deleted.

## III. RESULTS

### *A. Comparison of recognition performance and selection of optimal recognition performance*

Fig. 4 shows the average recognition accuracy of 11 finger movements with three classifiers for 5 subjects. Because of the differences among individuals, such as the different muscle levels, the influence of environment and other factors about the acquisition of sEMG signals, there is a slight difference in the recognition accuracy between different subjects for the same classifier, but it does not affect the selection of the best classifier. It can be seen from Fig. 4 that the recognition performance of ANN and SVM is better than that of kNN, and the recognition accuracy of kNN can only reach 80.81%. Fig. 4 also shows that the recognition accuracy of ANN is slightly higher than that of SVM. The average recognition accuracy of SVM is 87.10%, while that of ANN is 90.10%, and the recognition accuracy of subject A1 using ANN is 93.28%. This enables us to select ANN for the following research.

To better understand the recognition accuracy of 11 finger movements by ANN, Fig.5 shows the confusion matrix of one of the subjects. As can be seen from the figure, 11 finger movements can be effectively recognized, and the recognition rate is mostly more than 90%.

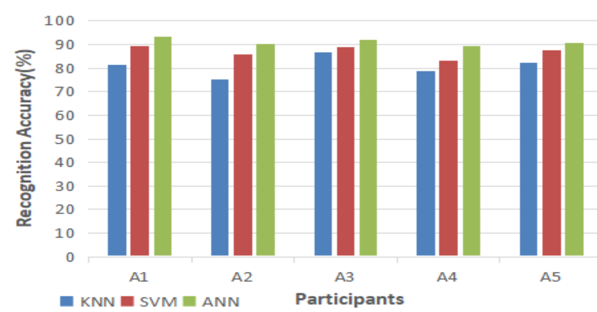



Fig. 4 Recognition results of three classification methods

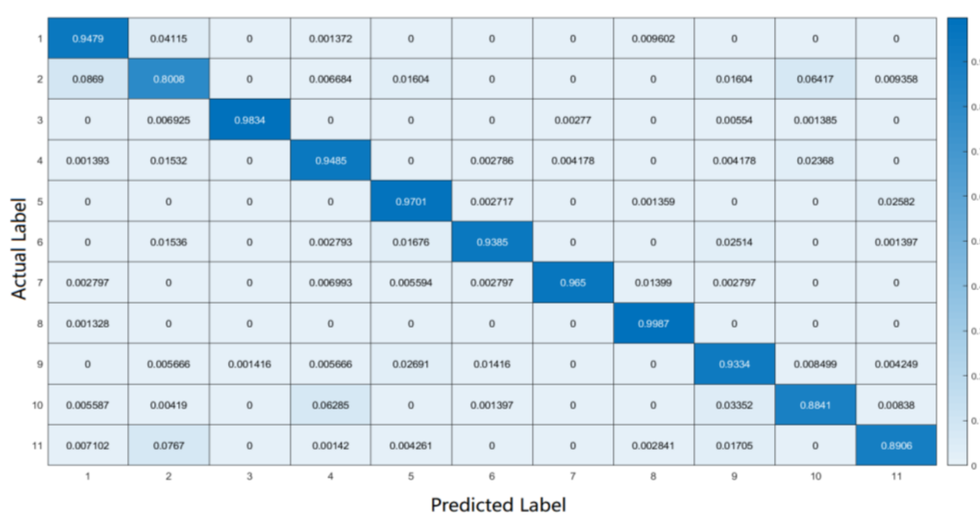



Fig. 5 Confusion matrix of A1

## B. Influence of the number of channels on the recognition accuracy

Fig.6 shows five subjects' recognition accuracy of different number of channels. This experiment illustrates the effect of number of channels on recognition accuracy, so that we can use the least number of channels to recognize finger motions. From the figure, we can see that the recognition accuracy increases with the increase of the number of channels. When the number of channels is less than 6, the recognition accuracy begins to decrease dramatically with the decrease of the number of channels. When using six channels, the recognition accuracy has reached more than 85%, and using seven channels has achieved similar results with eight channels. Therefore, Fig.6 shows that there is no significant difference between the accuracy provided by seven sEMG channels and that obtained by using more sEMG channels.

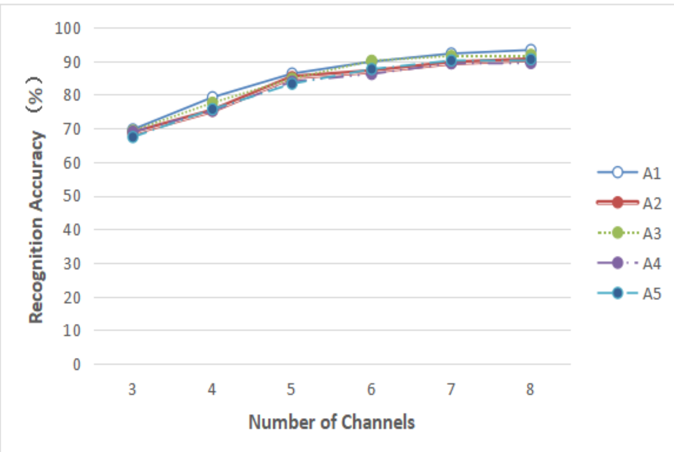



Fig. 6 Recognition results of different channels in five subjects

# IV. DISCUSSION

## A. Experimental results

The first numerical experiment evaluates recognition schemes. ANN achieves the best recognition results, which should benefit from the non-linear mapping ability of ANN. However, the selection of SVM kernel function and the processing of large-scale data is difficult to implement, so the result is a little worse than that of ANN. The recognition results of kNN are significantly worse than those of ANN and SVM.

The second numerical experiment solves the problem of how many sEMG channels are needed to control the dexterous prosthetic hand. Fig.6 shows that as the number of channels increases from 3 to 7, the recognition accuracy increases, and then remains stable. It shows that 7 sEMG channels are suitable for finger motion recognition. Through seven channels, five subjects obtained an accuracy rate of 90.52% for 11 classes of finger motions.

This study extracts time domain features from each channel and selects the appropriate classifier to provide the necessary information for recognizing a large number of motions. Compared with previous studies, this method leads to a higher $N_m/N_{ch}$ ratio (where $N_m$ is the number of finger movements and $N_{ch}$ is the number of sEMG channels). Table I summarizes previous studies and shows the $N_m/N_{ch}$ ratio in the last column.

The recognition results are similar to those reported by Tenore et al. [11]. They used one time domain feature and MLP pattern recognition method. For five intact-limbed subjects, the accuracy was 93.3%. However, they used 19 sEMG channels to recognize 12 classes of finger movements, and increased the accuracy to 94.1% by increasing the number of channels to 32 channels. For the only amputee, the reported accuracy was 87.8%. In our research, we use five time domain features, which together with ANN allowing for a reduction in the number of channels and high recognition accuracy. Anam et al. [15] achieved a higher $N_m/N_{ch}$ ratio than our work. However, they can achieve a higher recognition accuracy of 95.67% with only 5 movements, and when recognizing 8 movements, the recognition accuracy decreased to 86.73%.

TABLE I
The proposed method compared with previous studies

| Reference | $N_{ch}$ | $N_m$ | Recognition accuracy | Number of subjects | $N_m/N_{ch}$ |
|---|---|---|---|---|---|
| Jiang et al. [10] | 4 | 6 | 87% | 10 H | 1.5 |
| Tenore et al. [11] | 32<br>19 | 12<br>12 | 94.1%<br>87.8% | 5 H<br>1 A | 0.4<br>0.6 |
| Kanitz et al. [12] | 16 | 13 | 80% | 5 H and 1 A | 0.81 |
| Cipriani et al. [25] | 8 | 7 | 89%<br>79% | 5 H<br>5 A | 0.81<br>0.86 |
| Castro et al. [14] | 5 | 6 | 97% | 4 H | 1.2 |
| Anam et al. [15] | 2 | 5~8 | 86.73%~95.67% | 8 H | 2.5~4 |
| Fu et al.[13] | 6 | 8 | 92.2% | 5 H | 1.33 |
| This work | 7 | 11 | 90.50% | 5 H | 1.6 |

H=Healthy subject, A=Amputee person

In order to find the best seven channel locations, we follow the computational process of starting from multiple channels, and then gradually remove the channel with the least contribution. Through this method, we confirm that seven channels are good trade-off between the recognition accuracy of finger motions and the number of channels.

## B. Future work

There are still some deficiencies in our research. First, only offline pattern recognition is used. Subjects did not use virtual environment or actuated prosthesis for real-time display control. In addition, we only recognize single finger movements, but not combined finger movements and hand movements. The dexterous control of prosthetic hand requires accurate recognition of wrist movements, gesture movements and finger movements. Current results only show that the proposed scheme will achieve better performance than the other two alternatives.

At the same time, in this study, the collected sEMG signals are from the intact-limbed subjects, but there is no signal of amputees. Therefore, further studies need to obtain sEMG signals from amputees. The decoding and real-time response of sEMG signals of amputees will be the focus of our future work.

## V. CONCLUSION

This paper presents a research of using multi-channels sEMG to recognize finger movements for dexterous prosthetic hand control. We analyzed the sEMG data set of 5 subjects. Through time domain feature extraction and ANN classifier, 11 finger movements are recognized. The recognition accuracy can reach 91.10%. At the same time, the channel which contributes least to the recognition accuracy is eliminated step by step to find the best trade-off between the number of channels and the recognition accuracy. It is found that the recognition accuracy by seven channels was 90.52% and was no significant difference with more channels.

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