

Study on Motion Recognition for a Hand Rehabilitation Robot Based on sEMG Signals

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Abstract Robot-assisted self-rehabilitation training can overcome the shortcomings of clinical rehabilitation, which is significant for stroke patients. This paper proposed a hand robot rehabilitation training system based on surface electromyography (sEMG) signals. This study combines pattern recognition technology and biomedical technology to collect the sEMG signals of the daily movements of the stroke patients, and then pre-processes signals, feature extraction and pattern recognition classification, and recognizes the movement intention of the patients. Through the hand rehabilitation robot to help the affected side of the hand for rehabilitation training. In the online self-rehabilitation training, a certain motion mode performed by the contralateral side of the patient is obtained according to the pattern recognition offline trained classifier to obtain the classification result, and the motor-controlled hand robot is driven to perform the corresponding motion to realize the self-rehabilitation training. Finally, simulation experiments and volunteer rehabilitation training experiments were carried out. The experimental results show that the recognition rate of pattern recognition reaches $93.70\% \pm 2.22\%$. Compared with BP neural network in other literatures, our proposed wavelet neural network is better than 8% in the accuracy of recognition classification. This system we designed can effectively help patients with self-rehabilitation training.

Index Terms - Exoskeleton hand robot; sEMG signals; Hand motions recognition; Self-rehabilitation training.

I. INTRODUCTION

According to the China Stroke Prevention Report (2018), stroke is the first cause of years of life reduction in China. The number of stroke patients in China aged 40 and over has reached 12.42 million. According to the National Cardiovascular Professional Committee, 75% of the nation's surviving stroke patients have varying degrees of disability, which is a huge financial burden and social problems for the family and society.

In 2016, Florian Grimm, Armin Walter and Martin Spuler of Charlester University in Germany developed a multi-Joint Arm Exoskeleton rehabilitation robot [1], which is based on brain-computer interface, uses EMG control, and also uses virtual reality technology. Patients rely on the help of robots to complete virtual game tasks. This rehabilitation robot mainly helps patients to perform elbow flexion/extension and wrist internal/external rotation rehabilitation training. The disadvantage is that the robot is an end-to-end traction robot, which does not have the comfort and convenience of

exoskeleton robot. In [2], an inner-bottom sensor system is developed to determine various dynamic models of lower extremity exoskeleton in 2017. According to the results of human gait phase detection, the motion model of the lower extremity exoskeleton robot is analyzed. But it cannot be widely used in family rehabilitation training. In China, Song Aiguo of Southeast University and others developed a tele-rehabilitation training system in 2018 [3]. The team conducted rehabilitation training for patients with elbow and wrist joints, but their robots had less freedom, wore less comfortable, and could not meet the needs of self-rehabilitation training.

In response to the above problems, this paper proposes a portable exoskeleton hand rehabilitation robot including a finger. Based on this robot, a self-repaired hand rehabilitation training system based on surface electromyography signal is studied to help patients achieve active training. It improves the accuracy of classification and recognition of hand movements, and is suitable for use in homes and communities, reducing costs greatly.

Here is the structure of this article. The second part introduces the hand rehabilitation robot system, including the hand robot, the sEMG system, and the control circuit module. The third part of the pattern recognition classification. Including feature extraction methods, classification methods, and so on. The fourth part are experiments and results. The last part are conclusions.

II. THE SYSTEM OF REHABILITATION TRAINING

The training system is mainly consist of the sEMG signal acquisition system, motors and a controller and the exoskeleton hand rehabilitation robot.

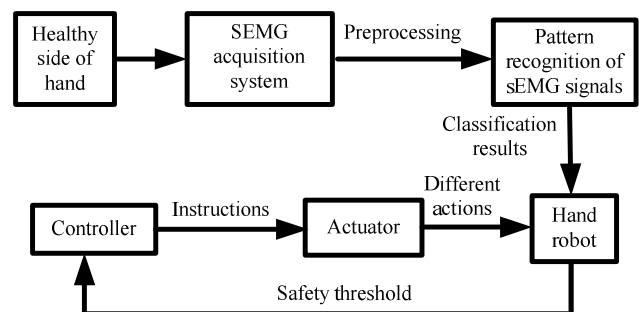


Fig. 1 Block diagram of self-rehabilitation training control system.

The rehabilitation robot realizes the self-rehabilitation training mode based on sEMG signals. The Fig. 1 is self-rehabilitation training control system block diagram.

A. The sEMG Acquisition System

The sEMG signals extracted in this paper was obtained by the surface electromyography acquisition system BIOFORCEN developed by Bioforcen Intelligent Technology Co. Ltd. provided by the research group.

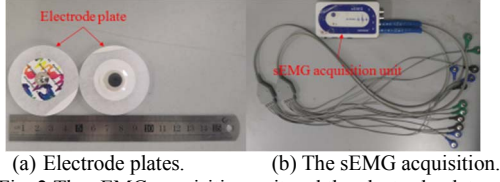


Fig. 2 The sEMG acquisition unit and the electrode plate.

The electrode plate is shown in Fig. 2a. The electrode plate is a circular patch with a diameter of 5*3cm, and the diameter of the signal recording surface was 10mm. The disposable electrode pads used in this study were produced by Shanghai Shenfeng Healthcare Products Co. Ltd. The hardware part of the sEMG signals acquisition mainly uses the energy converter to convert the acquired EMG signal into a bioelectric current that can be recognized by the software. The surface electromyography signal acquisition instrument extracts the signal through the surface patch electrode. Although there is a defect that the muscle fiber cannot be accurately obtained during the collection process, it has become the current collection of the myoelectric signal due to its small size and convenient use. Fig. 2 is the new generation JE-TB1620 myoelectric acquisition device used in this experiment.

B. Structure of the Exoskeleton Hand Rehabilitation Robot

The system is simple to operate, lightweight and portable. The exoskeleton finger rehabilitation robot in the robot system can be easily worn on the patient's hand. There are five stepping motors on the robot to realize the bending/stretching motion of the five fingers, which can achieve the maximum angle of the finger.

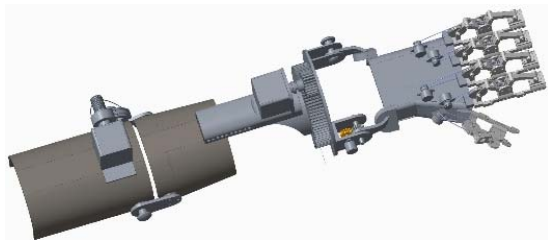


Fig. 3 The exoskeleton hand rehabilitation robot.

In addition, the robot also uses a wire rope drive to achieve long-distance power transmission, which can greatly reduce the load on the robot. The exoskeleton hand rehabilitation robot is shown in Fig. 3.

The system adopts the electric drive mode and adopts the stepping motor as the power source, which can realize more precise control, and can stop the motor at an arbitrary position,

that is, the patient's finger can be stopped at a certain position at any time. The exoskeleton finger rehabilitation robot has good flexibility, and the set bending/stretching motion can be smoothly performed during the movement.

III. HAND MOVEMENT CLASSIFICATION

A. Feature Extraction

Before the motion recognition, the feature extraction should be performed, and the signal can be most represented. The characteristic parts are extracted as eigenvalues, and they can effectively distinguish signals by high representation and high resolution. The purpose of feature extraction is to find finite dimensional data to characterize the characteristics of sEMG signals. In this study, the time domain analysis method, frequency domain analysis method and nonlinear dynamic analysis method - sample entropy are mainly introduced. Absolute mean value (MAV): The absolute average of the surface EMG signal reflects the intensity of the muscle action and the average intensity of the segment. Root mean square (RMS): The root mean square can represent the effective value of the sEMG signals [4], which reflects the distribution of limb movements and the strength of each part between muscle groups.

Sample Entropy is designed to reduce the error of approximate Entropy, which is more consistent with the known random part. That is, if one time series has higher values than another time series [5], it also has higher values for other sum values. Raw data for time series of length N , expressed as $\{a(i): 1 \leq i \leq N\}$.

1) Construct a set of vectors $X(1), X(2), \dots, X(N-m+1)$, where $X(i) = \{a(i), a(i+1), \dots, a(i+m)\}$.

2) The distance $d[X(i), X(j)]$ between vectors $X(i)$ and $X(j)$ is defined as the largest difference between the corresponding elements of two vectors, that is:

$$d[x(i), x(j)] = \max_{k=0 \sim m-1} |a(i+k) - (j+k)|. \quad (1)$$

3) For each $\{i: 1 \leq i \leq N-m+1\}$, the number of $d[X(i), X(j)] < r$ is counted as $N_m(i)$ and the ratio of the number to the total distance is calculated as $C_i^m(r) = N_m(i)/(N-m)$, under the condition that the allowable deviation is r .

4) The mean of all i is denoted as $\Phi_m(r)$.

$$\phi^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} C_i^m(r). \quad (2)$$

5) By increasing the dimension m by 1, the process of $m+1$ repeating 1)–4) is transformed into $C_i^{m+1}(r)$, $\Phi^{m+1}(r)$.

$$C_i^{m+1}(r) = N_{m+1}(r) / (N-m+1). \quad (3)$$

$$\phi^{m+1}(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} C_i^{m+1}(r). \quad (4)$$

6) In theory, SampEn (N, m, r) of the sample entropy of the program is as follows:

$$S(n \ m \ r) = \lim_{N \rightarrow \infty} \left\{ -\ln \left[\phi^{m+1}(r) - \phi^m(r) \right] \right\}. \quad (5)$$

In practice, it is impossible for N to take infinity. When N takes a finite value, it is estimated that:

$$S(m \ r) = -\ln \left[\phi^{m+1}(r) - \phi^m(r) \right]. \quad (6)$$

Therefore, in order to ensure that the calculated sample entropy has more reasonable statistical characteristics. According to Pincus theory, we choose r as 0.18 times of the original data and m as 2.

B. Pattern Recognition Classification

The wavelet neural network was first proposed by Zhang Qinghua of IRISA, a famous information science institution in France, in 1992. The model design mainly involves the selection of the best wavelet function as the learning ability of BP Neural Network [6]. In short, for the same learning task, the structure of WNN is simpler, the learning ability is stronger, the convergence speed is faster and the accuracy is higher. In this study, the wavelet neural network was used as a classifier to achieve the purpose of recognizing six hand movements.

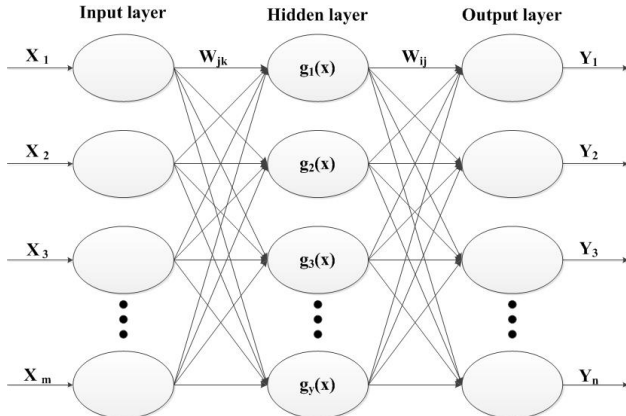


Fig. 4 Wavelet neural network (WNN).

The wavelet neural network model used in this paper is shown in Fig. 4. The method is to replace the transfer excitation function of neurons in the hidden layer of the neural network with the wavelet function, which fully inherits the good time-frequency localization property of the wavelet transform and the characteristics of the self-learning function of the neural network.

In Fig. 4, there are input layer, hidden layer and output layer. There are m neurons in the input layer, K neurons in the hidden layer and N neurons in the output layer. The input and output data of the network are represented by vectors X and Y, such as formulas (7) and (8):

$$X = \begin{bmatrix} X_1 & X_2 & X_3 & \dots & X_m \end{bmatrix}. \quad (7)$$

$$Y = \begin{bmatrix} Y_1 & Y_2 & Y_3 & \dots & Y_n \end{bmatrix}. \quad (8)$$

If X_k is the k-th input sample of the input layer, Y_i is the i-th output value of the output layer, W_{ij} is the weight of connecting the node i of the output layer and the node j of the hidden layer, and W_{jk} is the weight of connecting the node j of the hidden layer and the node k of the input layer. Let W_{j0} be the threshold of the j-th output layer node, W_{j0} is the j-th hidden layer node threshold (corresponding input $x_0=-1$), a_j is the scaling factor of the j-th hidden layer node, b_j is the translation factor of the j-th hidden layer node. In the formula, $i=1, 2, \dots, N$, then the wavelet neural network model is:

$$y_i = \sigma \left[\sum_{j=0}^n w_{ij} \psi_{a,b} \left(\sum_{k=0}^m w_{jk} x_k(t) \right) \right]. \quad (9)$$

$$\sigma(t) = \frac{1}{1 + e^{-t}}. \quad (10)$$

The input of the jth node of the hidden layer is expressed in formula (11). The output of the jth node of the hidden layer is related to the wavelet excitation function, as shown in formula (12). In formula (12), a_j and b_j are contraction factor and translation factor respectively. If $a_j > 1$, the wavelet function is stretched; if $0 < a_j < 1$, the wavelet function is compressed [7]. Because the wavelet neural network needs the function of stretching and compressing at the same time, the initial value range of a_j is between 0 and 2. The initial value range of translation factor b_j is between -6 and 6. Finally, the expression of output y_i is shown in formula (13).

$$net_j = \sum_{k=0}^m w_{jk} x_k. \quad (11)$$

$$\psi_{a,b}(net_j) = \psi \left(\frac{net_j - b_j}{a_j} \right). \quad (12)$$

$$y_i = \sigma \left[\sum_{j=0}^n w_{ij} \psi_{a,b}(net_j) \right]. \quad (13)$$

Given a sample set $\{(x_i, y_i)\}$, $i=1, 2, \dots, N$, the weight of the network is adjusted to minimize the following error objective function:

$$E(w) = \frac{1}{2} \sum_{i=1}^N \|Y_i - d_i\|^2. \quad (14)$$

Where: d_i is the output vector of the network; w is the weight vector composed of the ownership values in the network, $w \in R^l$. The gradient descent method is used to update the weights. It is simple to implement. When the objective function is a convex function, the solution of the gradient descent method is a global solution.

The excitation function is generally used between the layers of WNN, and the output of the upper layer is input to the next layer after the conversion of the excitation function. The neural network model is non-linear, and if no excitation function is used, then each layer is actually equivalent to matrix multiplication. Through the nonlinear excitation function, the WNN has more expressive power.

1) Morlet Wavelet:

$$h(t) = \cos(5t) \exp\left(-\frac{t^2}{2}\right). \quad (15)$$

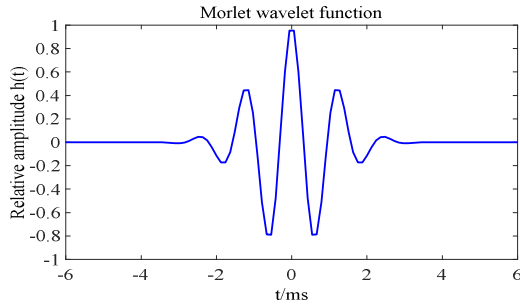


Fig. 5 Morlet wavelet.

2) Morlet1 Wavelet:

$$h(t) = \cos(1.75t) \exp\left(-\frac{t^2}{2}\right). \quad (16)$$

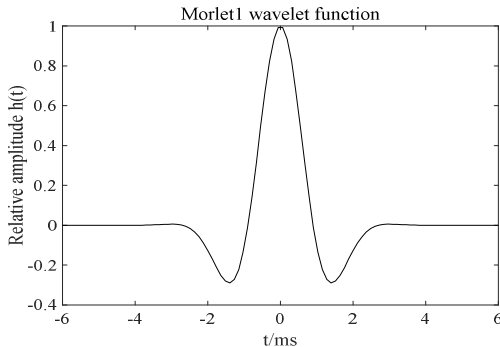


Fig. 6 Morlet1 wavelet.

3) Mexican Hat Function:

$$h(t) = (1 - t^2) \exp\left(-\frac{t^2}{2}\right). \quad (17)$$

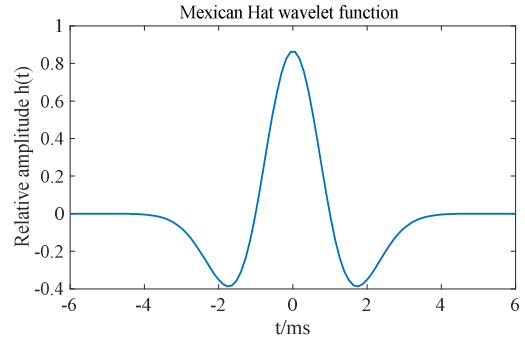


Fig. 7 Mexican Hat wavelet.

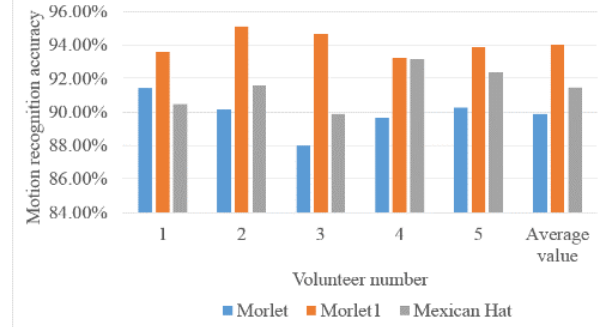


Fig. 8 The accuracy of different wavelet activation functions.

The general neural network excitation functions are sigmoid function, tanh function, and relu function [8]. When the wavelet neural network is used as the pattern recognition model, the above excitation function is replaced by the wavelet excitation function. In order to compare the influence of wavelet excitation function on network performance, we have selected three wavelet excitation functions [9]. Three kinds of wavelet activation functions are selected for comparison, as shown in Fig. 5, Fig. 6 and Fig. 7, respectively.

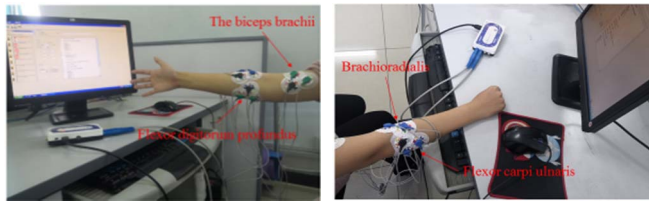
In order to ensure the consistency of the study, the same eigenvector values were used here, and five volunteers performed experiments to do the same six hand movements. According to the hand motion recognition result of Fig. 8, it can be seen that the morlet1 wavelet has the highest recognition rate as the excitation function, so the morlet1 wavelet is finally determined as the excitation function of the wavelet neural network. So far, the wavelet neural network model has been constructed.

IV. EXPERIMENTS AND RESULTS

A. sEMG Signals Acquisition

Before the collection experiment, gently polish the skin with sandpaper to remove the cuticle, and then wipe it with medical alcohol, so as to avoid the sweat on the skin surface and the cuticle will cause certain noise interference during the collection process and affect the accuracy of signal collection.

In the experiment, the distance between two adjacent electrodes depends on the size of the forearm of the subject, and is generally a center distance of 20-25 mm [10]. Since the energy of SEMG is mainly concentrated in 10-500Hz, The sampling frequency (1000 Hz) is used in this study. The Fig. 9 is the position of muscle of the upper limb.



(a) The palm side of hand. (b) The dorsal side of hand.
Fig.9 Position of muscles of the upper limb.

B. Arm Muscle Group Position and Hand Movements

The myoelectric signal is a bioelectrical signal generated during muscle contraction, and the contraction of muscle fibers at different locations will produce different movements [11]. Therefore, when selecting the muscle position, it is necessary to combine the hand movements to be identified to select the best collection of sEMG signals position.



Fig. 10 Schematic diagram of hand movements.

TABLE I
HAND MOVEMENTS AND CORRESPONDING MUSCLES

Hand movements	Major muscles
Hand open(HG)	flexor hallucis longus, flexor carpi ulnaris, The biceps brachii
Hand close(HC)	extensor ossis metacarpi pollicis, Brachioradialis,
OK gesture(OG)	Brachioradialis, palmaris longus, The biceps brachii
Eight gesture(EG)	musculus flexor digitorum superficialis, flexor digitorum profundus, The biceps brachii
Cylinder grasp(CG)	flexor hallucis longus, flexor digitorum profundus, flexor carpi ulnaris, The biceps brachii
Spherical grasp(SG)	Brachioradialis, flexor digitorum profundus, palmaris longus, The biceps brachii

This experiment selected six kinds of daily hand movements. Hand open (five fingers stretch); Hand close (five fingers bent); OK gesture (thumbs and forefinger flex, middle finger, ring finger and little finger stretch); Number eight gesture (thumb and index finger stretch, middle finger, ring finger and little finger bend); Hold the cylinder; Hold the ball, etc. Fig. 10 is schematic diagram of hand movements According to the Table 1, we selected four muscles for sEMG signals acquisition and experiment: brachioradialis, flexor carpi ulnaris, flexor digitorum profundus, the biceps brachii.

C. Results

In this study, a total of 10 healthy subjects volunteered to participate in the experiment, including three women and two men, with an average age of 24.8.

TABLE II
BASIC CONDITIONS OF THE SUBJECTS

Subjects	Gender	Age (full year)	Height (cm)	Weight (kg)	Physical condition (healthy, good, unhealthy)
1	man	26	176	64	good
2	man	25	190	90	good
3	man	23	180	75	healthy
4	man	25	187	76	healthy
5	woman	25	158	44	healthy
6	woman	23	164	50	healthy
7	woman	27	150	41	healthy
8	man	24	170	80	good
9	man	25	178	80	healthy
10	man	25	171	70	good

TABLE III
STATISTICS ON THE ACCURACY OF MOTION RECOGNITION

Subjects	HO	HC	OG	EG	CG	SG
1	91.64	92.56	91.87	89.36	90.35	94.00
2	96.00	95.69	94.55	96.35	94.36	95.96
3	91.58	94.35	92.45	94.25	91.98	92.62
4	92.24	91.54	94.36	95.95	94.35	95.43
5	93.89	93.59	91.47	92.87	94.63	91.35
6	97.25	97.63	91.13	93.78	91.85	95.76
7	91.12	98.31	98.36	93.68	94.65	92.78
8	89.21	95.35	94.25	94.36	92.69	97.69
9	94.58	94.21	97.45	91.23	92.75	92.35
10	93.67	91.38	96.32	95.86	89.86	91.19
Mean±SD	93.12 ±2.30	94.45 ±2.23	94.22 ±2.41	93.77 ±2.08	92.75 ±1.67	93.91 ±2.09

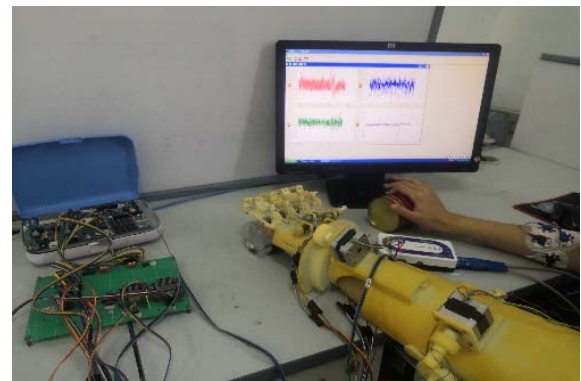


Fig. 11 Self-rehabilitation training experiment (cylinder grasp).

The right arm EMG signal was collected as the research object. The experimental process is shown in Fig. 11. The basic information of all subjects is summarized in Table II. In the experiment, each participant performed six hand movements in the same experimental environment: Hand open, Hand close, OK gesture, Eight gesture, Cylinder grasp and Spherical grasp.

Each hand motion lasted for 6 seconds, and the adjacent motion interval was 10 seconds. The task was repeated three times, with 180 seconds rest each time. Statistics on the accuracy of average hand motion recognition based on WNN in Table III.

From the Fig. 12, we can see that the accuracy of different actions is different. After calculation, the overall correct rate is $93.70\% \pm 2.22\%$. It shows that the training system has a higher correct rate. The Fig. 12 is box plot for the accuracy of hand motions recognition, we can see that the autonomous rehabilitation training system based on sEMG signals can help stroke patients to carry out self-rehabilitation training, with the highest recognition rate of hand close and the lowest recognition rate of grasping cylinders. It is important to keep the environment quiet during the acquisition process, so as to avoid the impact of noise on the recognition rate. After an experiment, the volunteers should get enough rest, otherwise muscle fatigue will occur. In the course of experiment, sometimes real-time is not very good. We will solve it in future research. Of course, because of the delay in MATLAB and motor, delay is inevitable. What we do is to make the delay as small as possible. Generally speaking, this system we designed can effectively help patients with self-rehabilitation training.

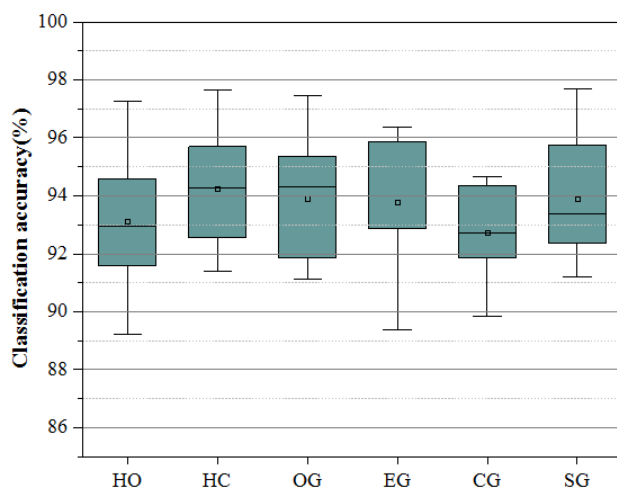


Fig. 12 Box plot for the accuracy of hand motions recognition.

V. CONCLUSION

In this paper, a self-rehabilitation training system for the exoskeleton hand rehabilitation robot based on surface electromyography signals is proposed. For most researchers, rehabilitation training is mainly applied to the upper limbs. Therefore, our original point mainly include rehabilitation training for hand and self-rehabilitation training, which can be applied to patients at different stages. The method of pattern recognition and classification of hand movements is emphasized. It solves the problem that most rehabilitation robots do not carry out rehabilitation training on their hands, and achieves self-rehabilitation training for stroke patients, thus effectively reducing the burden of medical staff and family members. Experiments show that the accuracy of hand movement classification and recognition reaches $93.70\% \pm$

2.22% . Wavelet neural network is determined by wavelet analysis theory, which can avoid the blindness of BP neural network structure design. Wavelet neural network has stronger learning ability and higher accuracy. We plan to use 5G technology to reduce delay time to help patients achieve long-distance rehabilitation training. Generally speaking, the system can effectively help stroke patients to carry out self-rehabilitation training, which will bring good news for stroke patients and contribute to the development of medicine.

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