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sEMG Pattern Recognition of Muscle Force of Upper Arm for Intelligent Bionic Limb Control

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Abstract

Two new feature extraction methods, window sample entropy and window kurtosis, were proposed, which mainly aims to complete the surface Electromyography (sEMG)-muscle force pattern recognition for intelligent bionic limb. The inspiration is drawn from physiological process of muscle force generation. Five hand movement tasks were implemented for sEMG-muscle force data record. With two classical features: Integrated Electromyography (IEMG) and Root Mean Square (RMS), two new features were fed into the wavelet neural network to predict the muscle force. To solve the issues that amputates' residual limb couldn't provide full train data for pattern recognition, it is proposed that force was predicted by neural network which is trained by contralateral data in this paper. The feasibility of the proposed features extraction methods was demonstrated by both ipsilateral and contralateral experimental results. The ipsilateral experimental results give very promising pattern classification accuracy with normalized mean square 0.58 ± 0.05. In addition, unilateral transradial amputees will benefit from the proposed method in the contralateral experiment, which probably helps them to train the intelligent bionic limb by their own sEMG.

Keywords: intelligent bionic limb, sEMG, muscle force, window sample entropy, window kurtosis

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1 Introduction

Currently, the use of the surface Electromyogram (sEMG) has drawn great attention as a control source for intelligent bionic limb. An artificial neural pathway built via sEMG adequately restored the lost function for people suffering from upper limb amputation[1–3]. Based on the performance analysis[4,5], a block diagram of ideal intelligent bionic hand device is conceived in Fig. 1, which includes human-device interface, control system and sensory feedback system. The performance of an intelligent bionic limb is influenced by many factors, including the comfort and fitness of the installation, the capability of the device, and the intuitiveness of the control system. It is the classification accuracy of the sEMG pattern recognition module that plays an important role in the intuitive and reliable control system[6–8]. In the past, a variety of methods are developed with respect to the pattern recognition between sEMG signal and human movements[9–11]. Some methods identified types of hand movement, others estimated different finger motions[12]. Whereas information extracted from sEMG is inadequate for intuitive and reliable control. The question that arises often under the results of these methods is that the prosthesis device just only mapped the intensity of movement by control schemes. It is mentioned that the intensity of movement performed at different force levels may be very different from one another[6], therefore, it presents a challenge to a pattern classifier. The dynamic information, such as muscle force, is supposed to be extracted from the sEMG signal in the intelligent bionic limb control.

There are two main ways to build relationship between sEMG and muscle force，mathematical model and neural network model. Lloyd and Besier[13] proposed a computational neuro musculoskeletal model of the human arm between EMG and muscle force on the basis of the body muscle physiological structure. Later, Wei *et al.*[14] developed a wavelet-based method to predict muscle forces in weightlifting based on the model proposed by Lloyd and Besier. It indeed needs to gather all types of ultrasound data[15] under muscle movement

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state to evaluate the muscle force by the skeletal muscle model, so it is not suitable to be directly used for intelligent bionic limb control. Kamavuako *et al*.[16] proposed the relationship research between needle electrode EMG and muscle force, and they pointed out that the linearly dependent coefficient between needle electrode EMG and muscle force is more than 0.9. Gurram *et al*.[17] used regression analysis of the power curve to research the human body muscle and concluded that the linearly dependent coefficient range between needle electrode EMG and muscle force is among 0.91 – 0.99. These results show that pattern recognition between sEMG and muscle force by the neural network is reasonable. Features of sEMG are fed into the black-box model of trained neural network combined with prior knowledge, the output is estimated muscle force, and no other data are required for the prediction.

According to the functional arrangement of muscle[18], as shown in Fig 2, the central nervous system of human beings controls muscle force through the adjustment of the recruitment of motor units and its firing rate. The motor unit is the smallest unit associated with the generation of muscle force. The muscle can be represented by motor units under the control of nerve axons originating from the central nervous system. The muscle fibers of each motor unit generate a motor unit force, and the sum of motor unit forces in a muscle produces the muscle force. sEMG is an overall show of motor unit potentials in a certain range, as the firing rate of motor unit increases, the sEMG signal complexity and the muscle force increase. In accordance with motor unit properties in structure, function and excitation during the activation that energize muscle force, a method for extracting features from sEMG for the pattern recognition of sEMG - muscle force is proposed here. As the important features to measure the complexity of sEMG

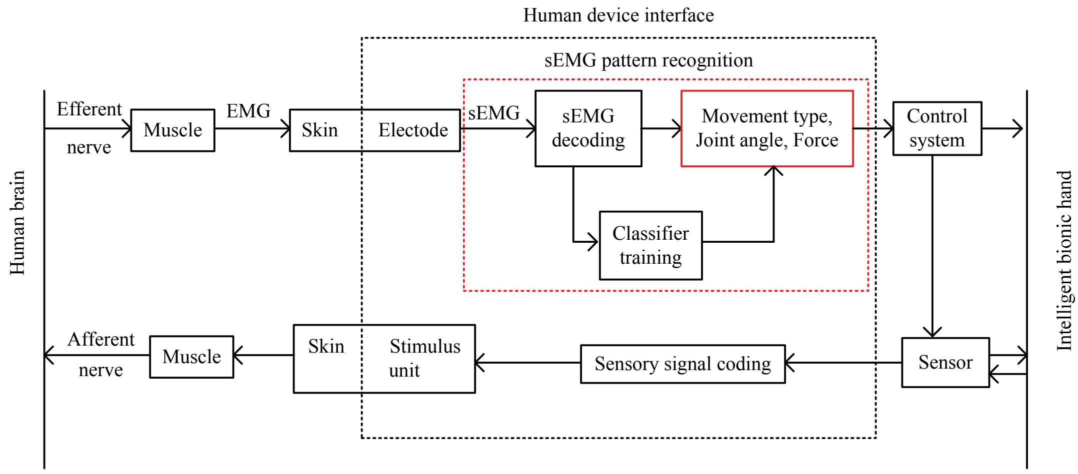


Fig. 1 Block diagram of intelligent bionic hand device.

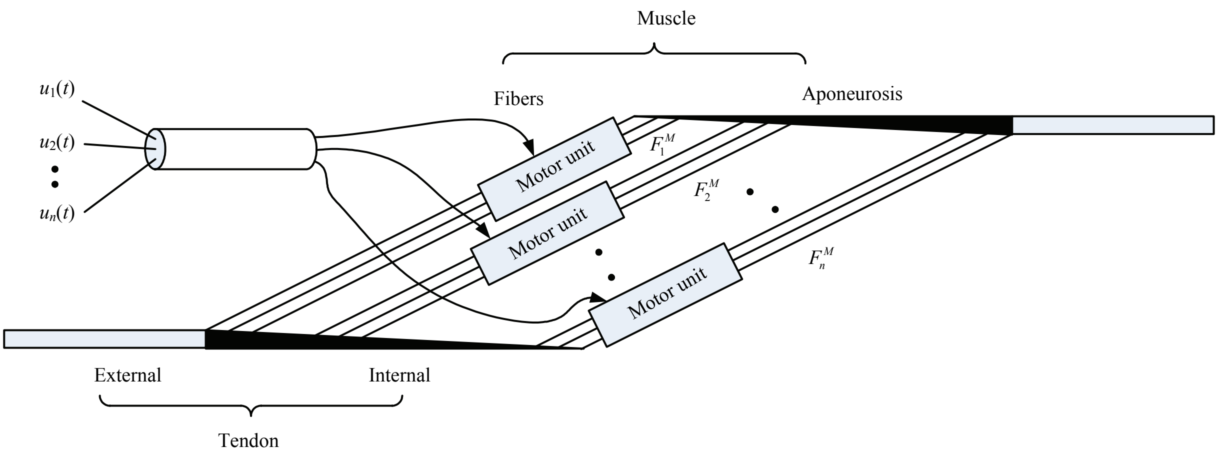


Fig. 2 Schema of the collective function of motor unit of one muscle[8].

signals, the window sample entropy on sEMG is used to estimate the muscle force. In the initial stage of motor unit potentials recruitment, the muscle force output changes a little bit and the sEMG signal complexity is low. This paper proposed using sEMG window kurtosis as time domain statistics feature takes part in pattern recognition in order to express better the impact of tiny variations of sEMG on the muscle force.

Due to the challenges to access an appropriate amputee population for research purposes, most investigations of sEMG pattern recognition used individuals with intact limbs instead of those with limb deficiencies. A recent study[19] showed relatively little difference between nondisabled and amputee subjects during classification by various methods, which implies that the results from nondisabled subjects can be generalized to amputatees. The amputatees' residual limb cannot provide full training input (sEMG) and output (hand grasp force) signals for the neural network in pattern recognition, therefore, the features of left hand's sEMG are fed into the classifier trained with right hand's signal to estimate muscle force. This scheme can be applied to unilateral transradial amputees.

2 Methods

As for sEMG-Muscle force pattern recognition method research, sEMG signal and muscle force are collected by different equipments, the sampling frequencies are not the same, and the acquired data volumes are different during the same period. From the point of view of exercise physiology[20], the purpose of the motor unit potential recruitment is to finish the relatively stable muscle force during a short time. It exists 200 ms – 300 ms delay between recruitment and output. According to the above situation, the feature of the sEMG signal in this paper is extracted in 200 ms continuously non overlap time window, then the feature value in continuous time window composes a feature vector corresponding to a muscle force output.

2.1 Window Sample Entropy (WSE)

Based on Grassberger's approximate entropy theory, sample entropy was proposed by Hariharan *et al.*[21]. It improved the precision and consistency of entropy algorithm, which reflects the new information generation rate in nonlinear dynamical system, and is suitable for the analysis of time series problems. Sample entropy shows the complexity of sEMG signal, that the higher complexity, the more muscle force output.

Based on the sample entropy concept, WSE algorithm of sEMG is proposed as follows.

(1) Let S be a time series of sEMG, the length of the series is k, the size of time window is w, sEMG signal can be represented as:

$$S = \sum_{x=1}^{n} s_x(i), \tag{1}$$

where x=(1, …, n) is the number of windows, $w \times x = k$;

(2) Let x=1, for time series $\{s_1(i)\}$ with N data points in S, according to i from small to large order to form a set of m dimension vectors:

$$\begin{gathered} \boldsymbol{s}_{1,\boldsymbol{m}}(i) = [s_1(1), s_1(2), \ldots, s_1(i+m-1)], \\ 1 \le i \le N-m. \end{gathered} \tag{2}$$

(3) In the vectors generated in step (2), the distance between two vectors is defined as:

$$\begin{gathered} \boldsymbol{d}\left[s_1(i), s_1(j)\right] = max[s_1(i+p) - s_1(j+p)], \\ 1 \le p \le m,\ 1 \le i, j \le N-m,\ i \ne j. \end{gathered} \tag{3}$$

(4) Giving a threshold r, count the number. $Q_1^m(i)$, of the distance $\boldsymbol{d}\left[s_1(i), s_1(j)\right] < r$, calculated in step (3), and the ratio of $Q_1^m(i)$ to the total number of the vectors, record as $B_{1,i}^m(r)$:

$$B_{1,i}^m(r) = (Q_1^m(i)) / (N-M-1). \tag{4}$$

(5) Average all $B_{1,i}^m(r)$ in the same time window,

$$B_1^m(r) = \frac{1}{N-M} \sum_{i=1}^{N-M} B_{1,i}^m(r). \tag{5}$$

(6) Increase the dimension in step (2) to m+1, repeat step (2) – (4), calculate $B_1^{m+1}(r)$, and then, the sample entropy of this series can be calculated as:

$$SampEn_1(N,m,r) = -\ln\left\{B^{m+1}{}_1(r) / B^{m}{}_1(r)\right\}. \tag{6}$$

(7) For series $s_x(i)$ of each time window in step (1), $x = (2, \ldots, n)$, repeat step (2)–(5), calculate the sample entropy of them, and the window sample entropy of S is:

$$SampEn_x\left(N,m,r\right)=-\ln\left\{\frac{B^{m+1}{}_x\left(r\right)}{B^{m}{}_x\left(r\right)}\right\}. \tag{7}$$

During the calculation, x, N, m, r need a given value according to actual value, from step (1), x is determined by the length of sEMG signal and the size of the window, w = 200 ms in this paper, and N depends on the window size and sample frequency F_s, $N= F_s \times w$, m=2, r=0.2. After the calculation, a window sample entropy vector can be extracted from the sEMG signal:

$$[SampEn_1, SampEn_2, \ldots, SampEn_x]$$

2.2 Window Kurtosis (WK)

sEMG is considered to be a random signal, the kurtosis of random signal is used to depict the steepness of signal. In the initial stage of motor unit recruitment, some sparse waveform unit can be observed in the sEMG signal which can be considered as the signal composed of single motor unit[22], so the kurtosis of sEMG is high. However, along with the increase in the recruited motor units, sEMG signal will be overlaid with complicated waveform, the kurtosis of sEMG decreases. Based on the kurtosis definition[23], window sample entropy algorithm of sEMG is proposed as:

$$K_x=\frac{E\left\{\left|s_x\left(i\right)\right|^4\right\}}{E^2\left\{\left|s_x\left(i\right)\right|^2\right\}}-3,\ \ x=(1,\ldots,n), \tag{8}$$

where $x = (1, \ldots, n)$ is the number of windows, the same as window sample entropy. After the calculation, a window kurtosis vector can be extracted from the sEMG signal: $[K_1, K_2, \ldots, K_x]$.

3 Experiments

3.1 Experimental schemes

Seven right-handed healthy volunteers, average age 22, whose upper limbs without neuromuscular history, are chosen in this experiment. The sEMG signals from flexor digitorum superficialis and flexor carpi radialis of the volunteers' upper limbs are collected during the experiment. These volunteers finished the grasp movement with the comfortable sitting posture. A volunteer puts arm on the front table, fixes the elbow at about 90 degrees, with forearm supporting desktop. A digital grip force meter is held in the volunteer's hand to measure and record the muscle force output. First, the volunteers are asked to complete two groups of the Right Hand Grow-keep Movement (RHGM) test. This experiment needs the volunteers to achieve maximum grip force within 3 sec and keep it for 3 sec. In order to avoid muscle fatigue, three min rest is needed for the interval of two events. The test case can help grasp the overall grip force situation of the volunteers, in the meantime, it can provide a reference for the average maximum grip force in the next experiment.

Later, five groups of right sEMG-muscle force test are conducted, each set of tasks for 3 min rest between. Experimental scheme is as follows:

(1) Right Hand Sectional Movement (RHSM): With initial grip force of 0 N, in the 0 sec – 8 sec the grip force increases 10 N every 2 sec and keeps for 2 sec.

(2) Right Hand On-off Movement (RHOM): In 0 sec – 4 sec the grip force increases from 0 N to 30 N in a constant speed, then in 4 sec – 8 sec the grip force reduces to 0 N in a constant speed.

(3) Right Hand Periodic Movement (RHPM): In 0 sec – 8 sec complete four sets 0 N – 30 N – 0 N griping action for 2 sec cycle.

(4) Right Hand Random Movement (RHRM): Complete 8 sec griping test in any grip force, maximum grip force is controlled in 30 N to avoid muscle fatigue.

Finally, the flexor digitorum superficialis and flexor carpi radialis sEMG-muscle force of the volunteers' left upper limbs are collected. Then the volunteers perform test (3) with their left hands (Left Hand Periodic Movement, LHPM). The grip force data will be used as reference for evaluation of the pattern recognition results. The volunteers must be in the non-fatigue experiment condition. If the experiment process can't attain the grip force requirements, the experiment will be canceled. The effective data obtained in the experiment are shown in Table 1. The third column of Table 1 is the number of the windows, generated by the sEMG feature extraction according to section **2**, which is the length of the feature vector.

Table 1 Details of the effective data

Experimental Project	Movement duration (s)	Number of windows	Number of effective data
RHGM	6	30	13
RHSM	8	40	5
RHOM	8	40	4
RHPM	8	40	5
RHRM	8	40	4
LHPM	8	40	7

3.2 Data processing

The dynamometer sampling frequency was set to 5 Hz, and the sEMG signals were filtered by 2 orders Butterworth filter. Among the various ways for sEMG feature extraction, the Integrated Electromyography (IEMG) and Root Mean Square (RMS) are able to respond to the changes of signal amplitude characteristics[24] and are widely used in the sEMG pattern recognition. The physiological process of muscle force output shows that there is an intimate relationship between the amplitude change and the signal output. Therefore, this paper combines these two characteristics as a joint participation in pattern recognition.

There are 13×30+(5+4+5+4)×40=1100 sets window feature obtained after the data processing of the six groups of right hand experiments (the first experiment was carried out on two groups). Corresponding to an output window muscle force, each group of left experimental data can obtain 7×40=280 sets window feature.

The experiment uses two channel sEMG, and each signal will extract the window sample entropy, window kurtosis, IEMG, and RMS. There are four characteristics in each channel signal, so each set of window contains eight features from two channels.

Fig. 3a gives the two channels of original sEMG collected in grow-keep task (RHGM), and the Fig. 3b is the corresponding muscle force output curve. There is no obvious connection between the sEMG and muscle force.

Four types of features through the two-channel sEMG feature extraction are given in the Fig. 4. They are window kurtosis, window sample entropy, IEMG and RMS from left to right. The time window is abscissa. It is evident that the relation between the multi-channel sEMG time-varying characteristic and the muscle force changes significantly from the figure. The window sample entropy, IEMG and RMS of the sEMG change as the muscle force's variation. The window kurtosis's change is relatively sharp in the initial raising phase of the motor unit potentials, and is steady in the muscle force maintaining phase. This appearance is in line with the expectation of the signal characteristics in section **2**.

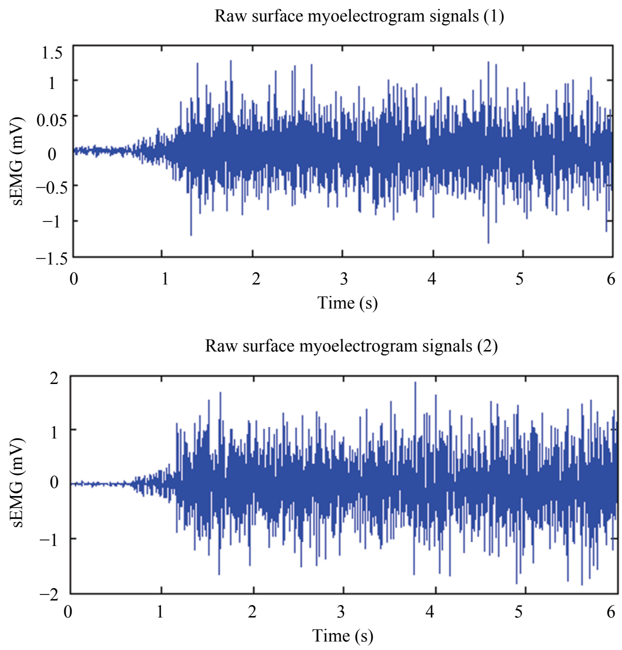
4 Results and discussion

The experiment implements the pattern recognition for right hand sEMG-muscle force data by the cross validation method, choosing one group experiment data as test data, and considering other data as the experimental samples. All left hand sEMG-muscle force data were assigned no training, all seven groups' data as test data. Features extracted were fed into the wavelet neural network, the hidden node number of wavelet neural networks is 6, and the training iterative learning is 100.

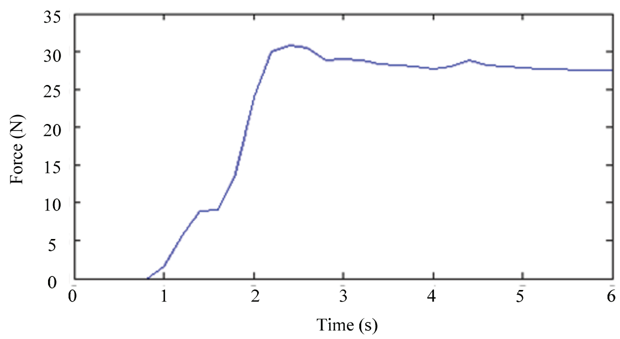
4.1 Ipsilateral prediction performance

Table 2 lists the Normalized Mean Squared Error (NMSE) between predicted muscle force and actual muscle force. The predicted muscle force was the output through wavelet neural networks which is trained by five kinds of right hand experiment schemes.

It can be seen from Table 2 that the predicted muscle force is close to actual muscle force in the five groups of experiments, the result error floating range is small among all the groups of experiments, and the predicted



(a) The two channels of original sEMG of RHGM



(b) Muscle force output curve of RHGM

Fig. 3 Original sEMG and muscle force curve.

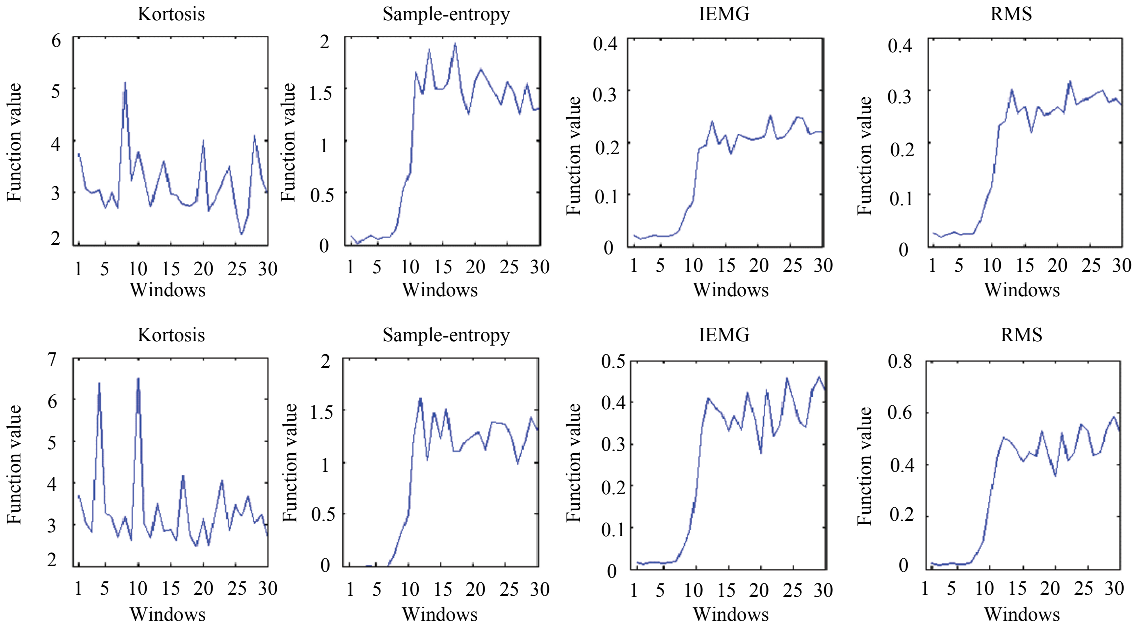


Fig. 4 Four types feature extracted from two-channel sEMG.

result is stable. Fig. 5 shows one prediction result in the RHOM with smallest error and one prediction result in RHRM with biggest error. It is seen that, although existing error, the predicted muscle force well tracks the changing trends of the actual muscle force. Both Table 2 and Fig. 5 suggest that the proposed method of force prediction is feasible.

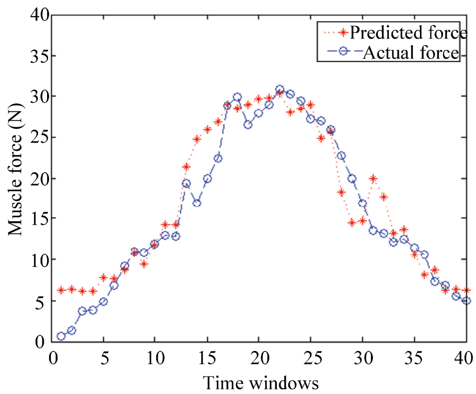
4.2 The effect of features

To verify the feature extraction methods proposed in this paper, four features are respectively carried on for sEMG-muscle force pattern recognition. Without distinguishing experiment types, only using features as index to calculate prediction errors, the results are shown in Table 3.

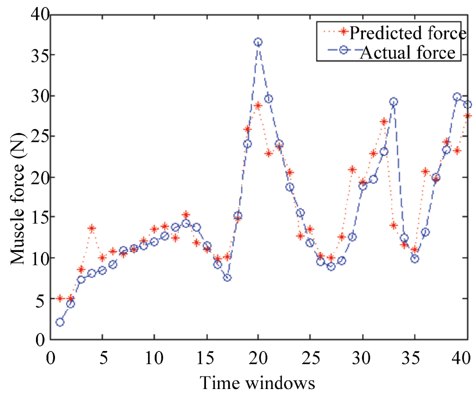
Table 3 show that the prediction effect using WSE and WK independently for muscle force prediction is better than using IEMG and RMS, demonstrating the two types of feature proposed in this paper contribute more to the stability of prediction. For the other two types of feature, especially RMS, the prediction error is larger, so the stability of the prediction is weak if RMS was chosen as an independent feature.

Table 2 Ipsilateral prediction performance

Project	NMSE (mean±se)	Project	NMSE (mean±se)
RHGM	0.76 ± 0.03	RHPM	0.85 ± 0.02
RHSM	0.63 ± 0.03	RHRM	0.87 ± 0.02
RHOM	0.58 ± 0.05		



(a) RHOM



(b) RHRM

Fig. 5 The comparison between predicted force and actual force (ipsilateral data).

Table 3 Four types of feature prediction performance

Feature	NMSE (mean±se)	Feature	NMSE (mean±se)
WSE	0.80±0.04	IEMG	0.82±0.07
WK	0.79±0.05	RMS	0.83±0.11

4.3 Contralateral prediction performance

Left hand periodic experimental data of the seven volunteers were recorded. The features extracted from the sEMG of the left hand were fed into the neural network trained by right hand data in section **4.1** to predict the muscle force of the left hand. The NMSE of the predicted results is 0.84 ± 0.03, which is nearly the same as ipsilateral data prediction performance. The stability of the prediction is good, which proves the feasibility that using the trained network of ipsilateral data to predict the relationship between contralateral sEMG and output muscle force. Fig. 6 shows the predicted results, it can be seen that the predicted muscle force is in good agreement with the actually measured force.

5 Conclusion

Inspired by physiological process of muscle force, a sEMG-muscle force pattern recognition method of upper arm is proposed for accurate estimation of muscle force through the features extracted from sEMG, on the basis of the bionic concept of kinesiology.

The proposed sEMG feature extraction methods of WSE and WK in this paper are different from the traditional methods of IEMG and RMS which only cut a small part of a long sEMG signal. This method tracks the sEMG signal during the time through building a continuous and non-overlapping window, and employs the features to follow the time-variation characteristic of the sEMG signal to display its change. The minimum muscle force predicts error in the experiment is 0.58 ± 0.05.

As the amputatees' residual limb couldn't provide full training data for pattern recognition, a solution was investigated that the relation between the features of sEMG and muscle force of the left hand was predicted via neural network trained by right hand data. The contralateral performance is very close to the ipsilateral performance. This scheme provides unilateral transradial amputees a possibility to train the intelligent bionic limb by using their own sEMG.

The proposed method may offer helpful clues to enhance the performance in pattern recognition module for intuitive control development of intelligent bionic hand.

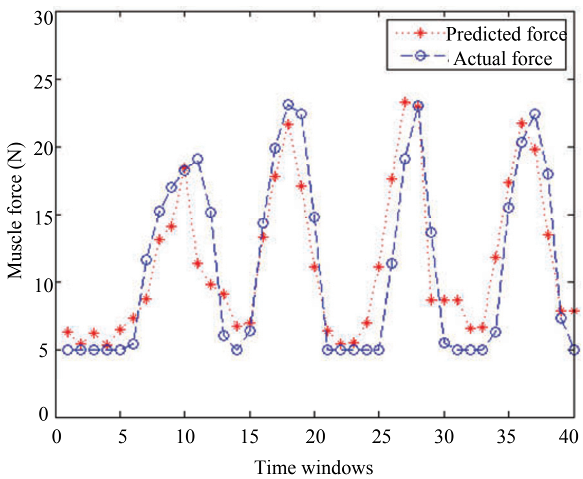


Fig. 6 The comparison between predicted force and actual force (contralateral data).

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