Grasping Force Control of Prosthetic Hand Based on PCA and SVM

Jian Ren[1], Chuanjiang Li[1(✉)], Huaiqi Huang[2,3], Peng Wang[1], Yanfei Zhu[1], Bin Wang[1], and Kang An[1]

[1] The College of Information, Mechanical and Electrical Engineering, Shanghai Normal University, Shanghai 201418, China
licj@shnu.edu.cn
[2] EPFL, 2002 Neuchâtel, Switzerland
[3] BFH, 2502 Biel, Switzerland

Abstract. This paper presents a control method of grasping force of prosthetic hand. Firstly, the correlated features of surface electromyogram (sEMG) signal that collected by MYO are calculated, and then principal component analysis (PCA) dimension reduction is processed. According to pattern classification model and sEMG-force regression model which based on support vector machine (SVM) to gain the force prediction value. In this approach, force is divided into different grades. The predicted force value is used as the given signal, and grasping force of prosthetic hand is controlled by a fuzzy controller, and combined with vibration feedback device to feedback grasping force value to patient's arm. The test results show that the method of prosthetic hand grasping force control is effective.

Keywords: MYO · PCA · sEMG-force · SVM · Fuzzy controller · Vibration feedback device

1 Introduction

The second national sample survey of disabled people shows that the number of amputation patients in China is as high as 2 million 260 thousand. A conservative estimate of the number of patients who need to install prosthetic hand up to more than 250 thousand people, therefore, it is necessary to study grasping force control in order to improve the functionality of prosthetic hand.

Currently, most research focus on identification of finger grasping mode, and few studies on force of prosthetic hand during grasping [1–3]. And some of the flexibility and operating sense of prosthetic hand are poor, many patients are reluctant to use the prosthetic hands. Commercial prosthetic hand adopts proportional control mode and determine the force directly according to the sEMG amplitude, but its accuracy is limited; Ahmet Erdemir established Del explicit model [4] of force-length-velocity-action potential, due to the complexity of human physiological structure, it is hard to establish an accurate model; Claudio Castellini used 10 electrodes to record sEMG data, but the more the number of electrodes, the more uncomfortable the patient.

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This paper adopts MYO [5] to collect sEMG. Grasping force is controlled by sEMG, which has the advantages of low cost, no invasion, convenience and high reliability. In addition, sEMG containing the information of user's action intention can be used as driving or feedback signal to improve movement effect and most prosthetic hands are controlled by sEMG [6–9]. From the literature, we know that force is contributed by many muscles [10, 11], and MYO has 8 electrodes that can meet the demand to collect multiple muscles at the same time. In addition, MYO has the advantages that it is simple and convenient to wear, thus high acceptance rate. We set sEMG and force as input and output, using SVM to establish nonlinear regression relationship between them. This method does not need complex modeling process, and shows good prediction effect [12–14], which is more practical than other modeling methods [9, 15–18]. For grasping force control part, we divide force into different grades, set the predicted force value as the given signal, use fuzzy control to control grip strength of prosthetic hand, and have vibration feedback device to feedback force grade value to patient's arm, which improve patient's sense of using prosthetic hand and realize accurate grasping. The whole structure is shown in Fig. 1.

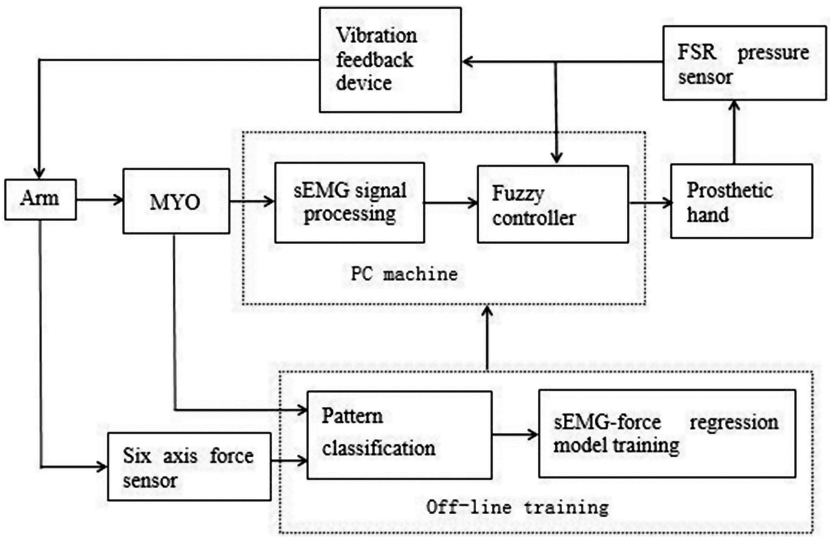

Fig. 1. The prosthetic hand grip control system diagram.

2 Methods

2.1 Signal Acquisition and Feature Extraction

In this method, the force is divided into eight different grades from 0 N to 16 N, and acquisition of sEMG of arm by MYO corresponding to each grade, and at the same time, acquisition of hand grip signal by a six axis force sensor [5], as shown in Fig. 2.

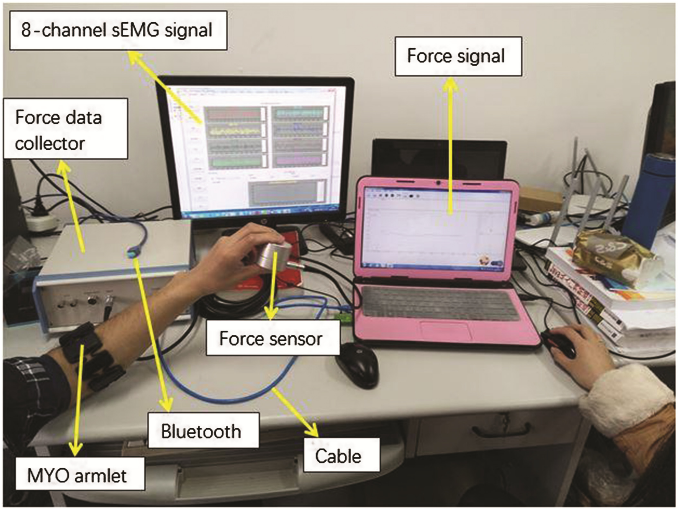

Fig. 2. sEMG and force signal acquisition.

According to time domain feature of sEMG to determine starting and ending time of movement, specific method is used to calculate the sum of Mean Absolute Value (MAV) of 8 channels sEMG, and then compare with the preset threshold value to judge the starting point and the ending point of action.

The accuracy of force prediction is related to features of sEMG, so it is essential to select suitable features [19, 20]. Most of sEMG analysis use time domain features, frequency domain features and other more complex features [21]. Features used in current study include four time domain features: MAV, Root Mean Square (RMS), Standard Deviation (SD), and Waveform Length (WL). MAV reflects the average intensity and the concentration of sEMG. RMS represents the contribution of each muscle organization in the process of the movement. SD can demonstrate the dispersion degree of a data set. WL can reflect the complexity of sEMG waveform, and the joint effect of sEMG amplitude, frequency and duration. Time domain calculation is simple, and that can ensure real-time grasping [22]. The calculation methods of each feature are as follows:

$$MAV_k = \frac{1}{N}\sum_{i=1}^{N} x(i) \tag{1}$$

$$RMS_k = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x(i)^2} \tag{2}$$

$$SD_k = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} (x(i)-\mu)^2} \tag{3}$$

$$WL_k = \sum_{i=1}^{N-1} |x(i+1)-x(i)| \tag{4}$$

Where x (i) is the sEMG data of each sample, N is the number of data of each channel, μ is the average of N data, k = 1, … , M, M is the number of channels.

2.2 PCA Dimension Reduction

Considering real-time, we adopt the method of PCA dimension reduction to reduce the computational complexity, shorten the computing time and improve grasping speed [23]. Between the beginning and ending time of one hand movement, a section of sEMG is intercepted as a one-dimensional signal sequence. Assuming that the number of the feature extracted is n, the dimension of the feature vector is $1 \times n$. Assuming $U \in R^{n \times k}$ is the dimension reduction matrix by PCA, the feature matrix multiplied by the dimension reduction matrix becomes $1 \times k$, namely from the original n-dimensional down to k-dimension. PCA can be used to analyze the main influencing factors from multiple sources and simplify complex problems [24].

2.3 Pattern Classification Model

To distinguish between 8 grades of grip strength,the pattern classification model is built, which is a 3-layer back propagation (BP) neural network. The number of input neurons is the dimension of feature matrix, denoted as K, the number of output neurons is the number of grip grades, denoted as C, the number of hidden layer neurons of H can be calculated by an empirical formula (5), and then adjust it according to the training precision. We can get weights and thresholds of pattern classification through training BP neural network model, and then save the weights and thresholds.

$$H = \sqrt{CK} \tag{5}$$

2.4 sEMG-Force Regression Model

In order to gain the grasping force value, we have to get force information from sEMG that is why to build sEMG-force model. The sEMG-force model is based on SVM, which uses sEMG data x $[x_1, x_2, \cdots \cdots x_n]$ (n element one dimensional vector) as input, and use force signal z as output to form several sample vectors $[x_1, x_2, \cdots \cdots x_n, z]$, then build the nonlinear regression relationship f from x to the target z: z = f (x). The following is a detailed introduction: Nonlinear regression function is f(x) = w•ϕ(x) +b, in the constraint condition of $\sum_{i=1}^{l} \left(\alpha_i - \alpha_i^*\right) = 0$, to optimize formula (6).

$$\begin{aligned} L(w, b, \xi) = -\frac{1}{2} \sum\nolimits_{i,j=1}^{l} (\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right) K\left(x_i, x_j\right) + \sum\nolimits_{i=1}^{l} \left(\alpha_i - \alpha_i^*\right) y_i \\ - \sum\nolimits_{i=1}^{l} \left(\alpha_i + \alpha_i^*\right) \varepsilon \end{aligned} \tag{6}$$

In which, $w = \sum_{i=1}^{l} \left(\alpha_i - \alpha_i^*\right) \phi\left(x_i\right)$, combined with Karush-Kuhn-Tucker optimality condition, we can get the nonlinear regression function:

$$f(x) = \sum_{i=1}^{l} \left(\alpha_i - \alpha_i^*\right) K\left(x_i, x\right) + b \tag{7}$$

Where $K(x_i, x_j)$ is a kernel function,which is the sample inner product of ϕ space by using Gaussian kernel function: $K(x_i, x_j) = \left\langle \varphi\left(x_i\right), \varphi\left(x_j\right) \right\rangle = \exp\left(-\gamma \left\| x_i - x_j \right\|^2\right)$, where γ is kernel function parameter. α and α^* can be calculated from training sample space $\left\{ \left[x_1, z_1\right], \cdots, \left[x_l, z_l\right] \right\}$.

2.5 Grasping Force Control

The signal is collected from one healthy subject, which include eight grades of grasping force read through a six-axis force sensor, and eight channels sEMG of sEMG signal gathered from MYO corresponding to eight grades. Extracting time domain features, then feature matrix is used as a sample for training pattern classification model, and feature matrix with force data are used to construct sample for sEMG-force regression model training, then the parameters of each model is saved and written to the PC. After the preparation below, patient can wear MYO to collect sEMG, read sEMG by PC machine and process sEMG as mentioned earlier. And then pattern classification model will recognize which grade the signal belongs to, and then the signal will be send to the corresponding grade of sEMG-force model to predict force value. What follows is that setting the predicted force value as the given signal to control grasping force of prosthetic hand by fuzzy control, and the size of grip strength of prosthetic hand induced by the FSR pressure sensor on prosthetic hand. Then vibration feedback device changed the size to force grade value, and feedback it to patient's arm, in order to make patient get the real grasping value grade and adjust grip strength according to it, so that can achieve accurate grasping.

3 Results

In order to reduce calculation time, ensure real-time grasping and improve force prediction effectiveness, comparison of pattern recognition rate of eight grades force among the number of sEMG channel, feature and PCA dimension reduction has been analyzed. By mapping eight channels of sEMG, we observed that there are three channels signal fluctuated obviously, which means these three channels signal relatively sensitive and ideal for grasping movement. The recognition of reading eight and three channels of sEMG, extracting four time domain features, and their eight grades force pattern recognition are shown in Fig. 3.

For the eight channels sEMG, result of four features is shown as the blue bars in Fig. 3, result of three features is shown in Fig. 4. The results show that for the eight channels signal, the selection and number of features have little effect on recognition rate. Probably because

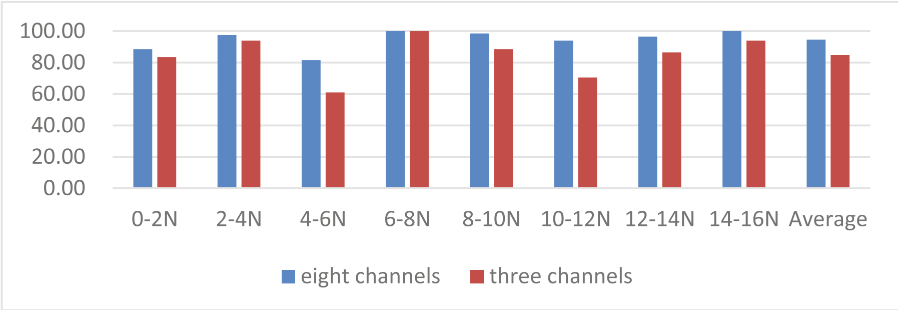

Fig. 3. Pattern recognition rate of different channel number using four features. The bars with different colors represent different channels of sEMG signal. The X-axis represents the magnitude of the forces at eight different levels, and Average represents average recognition rate of the eight grades. The Y-axis represents recognition rate (%). The X-axis and Y-axis in Figs. 4 and 5 have the same meaning. (Color figure online)

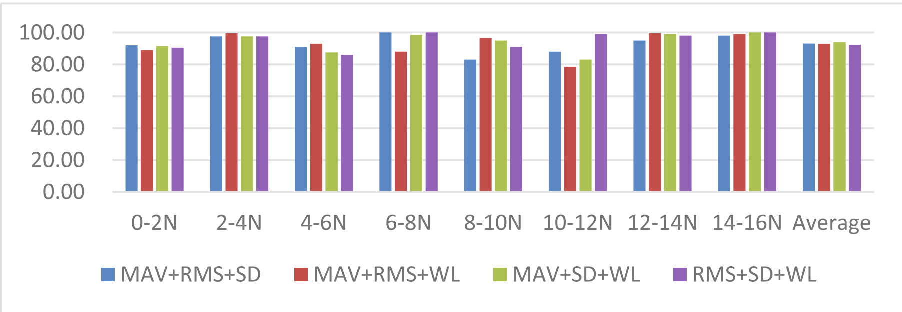

Fig. 4. Pattern recognition rate of eight channels with three features. The bars with different colors represent the recognition of combinations of different three features.

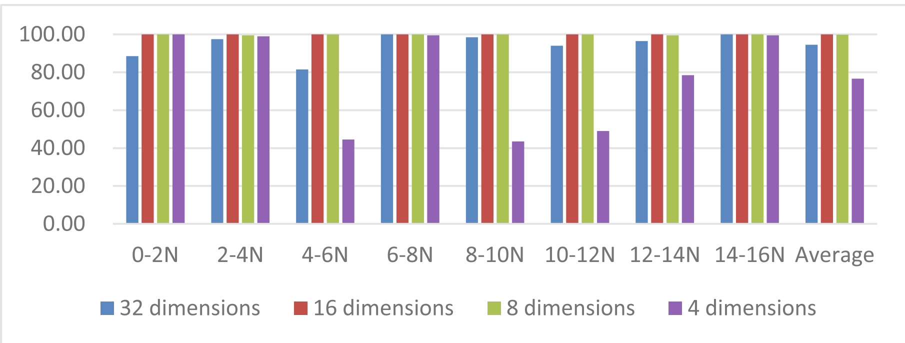

Fig. 5. Pattern recognition rate of eight channels with four features reduced by PCA to different dimensions. The bars with different colors represent the recognition of different dimensions.

For the eight channels sEMG, each channel four features are extracted, then we can get a 32-dimension feature matrix, and reduce dimension by PCA to 16, 8 and 4. Figure 5 shows the result of the four cases. Experimental results show that the recognition rate of 16 and 8 dimensions are better than that of 32 and 4 dimensions; In addition, the time of reducing dimension from 32 to 16 or 8 is the same, but the calculation of 16 dimensions is much larger than that of 8, so we choose to sacrifice a little bit of recognition rate in exchange for higher real-time grasping.

Through the above analysis: when grasping force control of prosthetic hand, we adopt the method of reducing dimension to 8 dimensions by PCA of the feature vector of eight channels and four features. And as shown in Fig. 6 is the prediction result of the grip strength of the eight grades. Which shows that the predicted value of each grade force is almost in the range of the corresponding force. On the whole, it displays a good force prediction effect. And therefore,

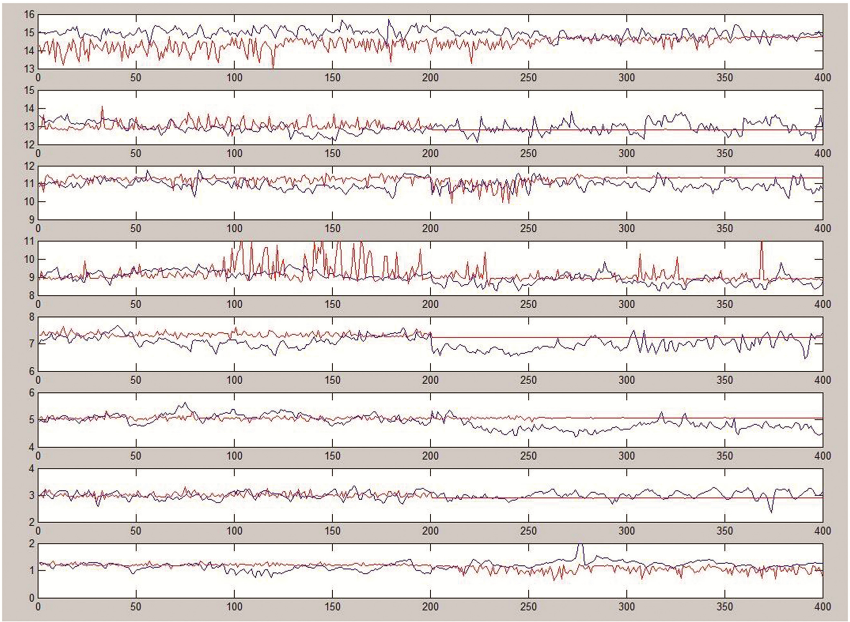

Fig. 6. The prediction results of the grip strength of the eight grades. The X-axis represents sampling point of force signal, and Y-axis represents eight grades of force size. The blue curve represents actual grasping force value, and the red curve represents predicted grasping force value. (Color figure online)

4 Conclusion

In this paper, we proposed a control method of hand grasping force of prosthetic hand based on PCA and SVM, using PCA to reduce dimension of time domain feature matrix, forecasting grasping strength by establishing regression model between sEMG and force based on SVM; The calculation of time domain is simple, in addition, PCA reduces the amount of computation and shortens calculation time, which provides real-time for the control of prosthesis grasping, and the method of establishing regression model by SVM is simple and also get a good prediction effect. Using fuzzy controller to control grasping force of prosthesis hand and vibration feedback device to feedback force value to patient's arm can improve the patient's sense of using prosthetic hand. The experiment shows that this approach is an effective control method of prosthesis hand grip.

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