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The recognition of grasping force using LDA

Nianfeng Wang*, Kunyi Lao, Xinhao Zhang, Jinfan Lin, Xianmin Zhang*

Guangdong Province Key Laboratory of Precision Equipment and Manufacturing Technology, South China University of Technology, Guangzhou, Guangdong 510640, PR China

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ABSTRACT

This paper proposes an EMG recognition system of grasping force on the basis of the pattern recognition, which can classify the surface electromyography (sEMG) signals from 2 electrodes and recognize the grasping force. Ten characteristics in time domain and frequency domain are chosen as the primary features to combine feature sets, to obtain an optimal feature set. The linear discriminant analysis (LDA) is used to reduce the dimension of the features vector to a one-dimensional vector matrix, and pattern recognition to classify and recognize it. In online recognition, to obtain continuous recognition values, the quadratic polynomial fitting is utilized to find the relationship between the one-dimensional vector matrix and grasping forces.

1. Introduction

Myoelectric control has been widely used to control peripheral devices [1,2], especially prosthetic limb [3], as the surface electromyography (sEMG) signal is a noninvasive electrical biosignal and can represent the muscles activities. The EMG control get great development from using the correlation between EMG signal amplitude and gestures to using pattern recognition [4]. The pattern recognition method in a supervised way is widely employed to control the prosthetic hands to perform different prehensile gestures. The preprocessing parts of the pattern recognition method include data preprocessing, data windowing, feature extraction and classification [4,5]. The corresponding features are extracted from various muscle activities, and then the features are assigned to classes which represent relevant limb motions, that are patterns. These patterns are learned by an algorithm which is then used to classify the limb motions. In our previous research [6,7], a myoelectric control system using 2 acquisition electrodes which can classify 8 prehensile hand gestures has been built. Pattern recognition is employed with Mean Absolute Value (MAV), Variance (VAR), the fourth-order Autoregressive Coefficient (AR) and Sample Entropy (SampEn) as the optimal features set. LDA is utilized to reduce the dimension of the features. A combination of pre-smoothing and post-smoothing method makes the recognition of continuous gestures possible. Liu et al. proposed a method, namely Mixed-LDA, which computes the parameters of LDA through combining the model estimated on the incoming training samples of the current day with the prior models available from earlier days [8]. Lin et al. proposed an algorithm only needs very limited training data using shrinkage approach, information transfer rate and K-L divergence [9]. Uslu and Baydere proposed a novel real time activity recognition approach, called RAM, presenting a non-invasive method with a single accelerometer [10]. Rubiano et al. proposed a new elbow flexion and extension identification scheme [11].

In order to grasping objects stably, the functions of the prosthetic hand are not only recognizing the relevant motion that the sEMG signals represent, but also estimating the grasping force to hold the object. Therefore, the information of grasping force should be extracted from the sEMG signal to improve the performance of myoelectric control system. To find the relationship between sEMG and grasping force, there are mainly two ways, mathematic model method [12–16] and machine learning method [17]. The former builds mathematic model between EMG signals, muscle-based model and muscle force, and predicts the grasping force. The later finds the nonlinear relationship with EMG signals as input and muscle force as output. The common methods employed are multiple nonlinear regression [17], support vector machine (SVM) [18–20], artificial neural network (ANN) [21,22], gene expression programming (GEP) [23], etc. Manal et al. presented a formulation for a one-parameter transformation model that accounted for the type of physiological nonlinearities observed at low levels of force [14]. Wei et al. developed a wavelet-based method to predict muscle forces from sEMG signals [15]. Fang et al. established a mathematic model for muscle activation extraction to describe the relation-

* Corresponding authors.
E-mail addresses: menfwang@scut.edu.cn (N. Wang), zhangxm@scut.edu.cn (X. Zhang).

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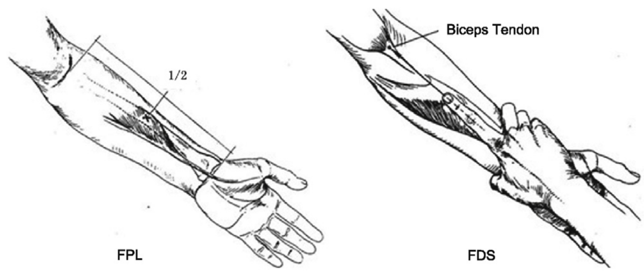

Fig. 1. The position of FPL and FDS [24].

ship between finger pinch forces and sEMG signal, and the genetic algorithm was employed to optimise the coefficients [16]. Yang et al. demonstrated the use of Locally Weighted Projection Regression (LWPR), ANN and SVM to represent relationship of the hand's enveloping force and 6 channel sEMG signals, and showed that the SVM method is better than LWPR and ANN to estimate hand grasping force from sEMG signals for force control [18,19]. Choi et al. implemented an ANN to map the SEMG at three myoelectric sites to the palmar pinch force, with a Normalized Root Mean Squared Error (NRMSE) of 0.08 [20]. Xu et al. used Integrated Electromyography (IEMG), Root Mean Square (RMS), window sample entropy (WSE) and window kurtosis (WK) to feed into the wavelet neural network to predict the muscle force with a normalized mean square of 0.58 [22]. Yang et al. utilized Gene Expression Programming (GEP) to derive a new empirical model of handgrip sEMGCforce relationship, using the input vectors of 10 features of the sEMG time domain extracted from homogeneous subsets, which showed that the proposed GEP model is relatively fast, simple and excellent for predicting handgrip forces based on sEMG signals [23].

To improve the myoelectric control system, the grasping force estimation is added. The developed EMG recognition system can classify the sEMG signals and recognize the grasping force. An optimal feature set of grasping force is obtained from ten characteristics in time domain and frequency domain by experiments. In online recognition, the quadratic polynomial fitting is utilized to find the relationship between the one-dimensional vector matrix and grasping force.

2. Methods

2.1. Data collection

According to the range of grasping forces observed in human daily-life activities, the myoelectric control system identifies 6 grasping forces (0 kg, 2 kg, 4 kg, 6 kg, 8 kg and 10 kg). The flexor pollicis longus (FPL) and the flexor digitorum surperficials (FDS) (Fig. 1) are selected as the relevant muscles to acquire the surface electromyography (sEMG) signals. Biometrics DataLog (Fig. 2), including two SX230 bipolar myoelectric sensors, a G100 grasping force sensor, a DataLog data collector, and the Biometrics DataLog software, are used to collect the sEMG signals.

2.2. Feature extraction

Long EMG signals for the classification will cause a sense of perceptible delay. Therefore, data windowing is used as the preprocess of the EMG signals. Due to the instability and randomness of EMG signals, it is difficult to acquire a right decision of grasping force from only one data window. Constructing a sequence of decisions and making a final prediction may raise the accuracy but needs more time. The overlapping windowing scheme is put forward to solve the problem. A data windowing in the scheme contains a majority of EMG signals of the previous window and EMG signals in the incremental part. Compared with the general windowing scheme, the operation time of the overlapping windowing scheme is shorter, which could meet the delay requirement that the time interval is less than 300 ms. What is more, the overlapping windowing scheme also improves the utilization of EMG signals. The window length is 250 ms and the increment is 70 ms in this paper.

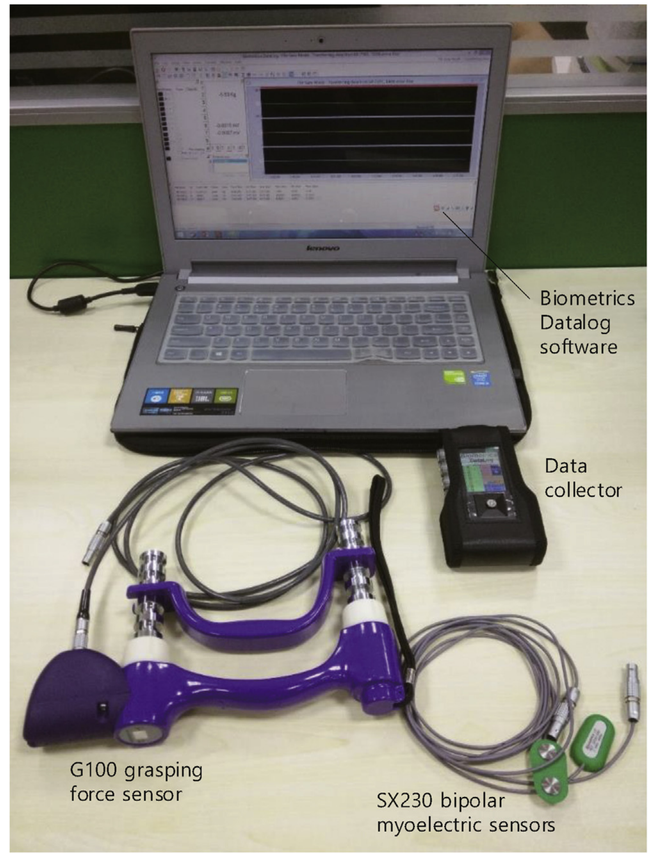

Fig. 2. Biometrics DataLog.

The accuracy of the pattern recognition in sEMG greatly depends on the selection and extraction of features [1]. In this paper, ten features including MAV, VAR, RMS, Waveform Length (WL), Wilson Amplitude (WAMP), Zero Crossings (ZC), AR, SE, Mean Power (MNP) and Median Frequency (MDF) are chosen to analyze the accuracy rate of the pattern recognition.

MAV can be calculated by the following formula:

$$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N}|s(i)| \tag{1}$$

where $s(i)\{1 \le i \le N\}$ is used to denote the ith point in a sEMG window. N is the length of the window.

In theory, the mean of the sEMG signals is zero. Therefore, VAR of the sEMG signals can be obtained by:

$$\mathrm{VAR} = \frac{1}{N-1}\sum_{i=1}^{N}s(i)^2 \tag{2}$$

The definition of RMS is shown in following equation.

$$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}s(i)^2} \tag{3}$$