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Realtime recognition of multi-finger prehensile gestures

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ABSTRACT

This paper presents an on-line myoelectric control system which can classify eight prehensile hand gestures with only two electrodes. The overlapping windowing scheme is adopted in the system leading a continuous decisions flow. We choose mean absolute value (MAV), variance (VAR), the fourth-order autoregressive (AR) coefficient and Sample entropy (SampEn) as the feature set and utilize the linear discriminant analysis (LDA) to reduce the dimension and obtain the projected feature sets. The current projected feature set and the previous one are “pre-smoothed” before the classification, and then a decision is generated by LDA classifier. To get the final decision from the decisions flow, the current decision and *m* previous decisions are “post-smoothed”. The method mentioned above can obtain a 99.04% off-line accuracy rate and a 97.35% on-line accuracy rate for individual gesture. By choosing a proper value of *m*, this method can also get a 99.79% accuracy rate for on-line recognition of complex sequences of hand gestures without interruption. In addition, a virtual hand has been developed to display the on-line recognition result visually, and a proper control strategy is proposed to realize the continuous switch of hand gestures.

1. Introduction

The surface electromyography (sEMG) signal is a noninvasive electrical biosignal which can represent the muscles activities. As a type of easy-acquired signal, it has been widely used to control peripheral devices [1,2], especially prosthetic limb [3]. During the last decade, several mulitifunctional anthropomorphic prosthetic hands have been developed by some companies and research institutions [4–9], such as i-Limb hand [4] and SmartHand [6]. Their appearance and size are similar to human hand and they have 8-degrees of freedom at least. To control these prosthetic hands to perform prehensile gestures for activities of daily living, the pattern-recognition method in a supervised way is widely employed [10]. This method includes some fundamental processing parts [10] (Fig. 1): data preprocessing, data windowing, feature extraction, and classification.

The corresponding features can be extracted from different types of muscle activities, and then these features are assigned to classes that represent corresponding limb motions, which are the patterns. These patterns are learned by an algorithm using some part of the features, and the algorithm is then used to classify the limb motions according to further features [11].

The accuracy of the motion classification depends very much on the feature selection and extraction. A variety of EMG features have been proposed. They can be divided into three categories: time domain, frequency domain, and time-frequency domain [1]. Each kind of features can represent the property of sEMG to some extent; however, due to the nonstationarity of the sEMG signals, it is very difficult for only one feature to reflect the most intrinsic property of the measured sEMG signals of a motion perfectly [12]. Many researches tend to use feature set (the combination of different features) to describe the sEMG signals of a certain motion [13–19]. Phinyomark et al. [13] explored many combinations of different features and compared their performance in the recognition of ten upper limb motions. It is concluded that the combination of SampEn, the fourth order cepstrum coefficients (CC), root mean square (RMS) and waveform length (WL) was considered the best robust multiple-feature set. Ju et al. [14] successfully recognized different hand grasps and in-hand manipulations by using multiple features which included Willison Amplitude (WAMP) and Determinism (DET).

The effectiveness of the algorithm for off-line sEMG pattern recognition has been proven by many researches [16–18,20–24]. However, the biggest challenge is to gain a satisfactory accuracy rate for on-line sEMG recognition. In the case of realtime control of a prosthetic hand, a high accuracy rate is essential, and controlling

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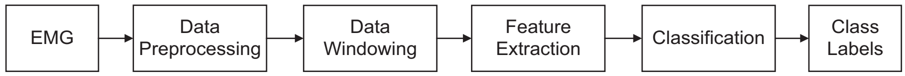

Fig. 1. Block diagram of EMG pattern recognition [10].

the prosthetic hand in an intuitive and close-to natural way should also be considered carefully. Khushaba et al. [15] used various features and LIBSVM classifier to recognize ten individual fingers and combined finger movements which gained approximately 92% off-line and approximately 90% on-line classification accuracies. Chen and Wang [16] successfully classified ten Chinese number gestures on-line. Although they both realized the realtime recognition of different hand motions, the relax gesture must be inserted between every two hand motions when the realtime recognition was running. It does not meet the grasp habit of a real human hand and the switch of hand gestures should be continuous.

Based on our previous research on the off-line recognition [22], we explore a realtime hand gesture recognition system which is more intuitive and natural for users to control the prosthetic hand. First, we adopt the overlapping windowing shceme [25] and use the feature set including MAV, VAR, the 4th AR and SampEn for the off-line training phase. Second, a post-processing method is used to process the continuous decisions for the realtime recognition. Finally, a virtual hand model is developed to show the recognition result of the realtime system visually, and a proper control strategy is employed to ensure that the virtual hand can change its gesture continuously without being interrupted by the rest gesture.

2. Methods

2.1. Data collection

The eight prehensile hand gestures [22] including: cylindrical, hook, lateral, point, spherical, tripod, tip and rest, as illustrated in Fig. 2, were designed to test the recognition system. Their main functions were described as follows:

1 Cylindrical: To grasp cylindrical objects, such as an ordinary cup.
2 Hook: To carry objects, such as a handbag.
3 Lateral: To hold flat objects, such as a credit card.
4 Point: To point a direction or hold something spindly, such as a knife.
5 Rest: When there is no muscle contraction, the prothesis hand extend all fingers to carry something, such as a book.
6 Spherical: To grasp small round objects, like a tennis ball.
7 Tripod: To carry small objects.
8 Tip: To pinch very small objects, such as a needle.

As these gestures mainly involve the flexion of both the thumb and the rest four fingers, we chose the flexor pollicis longus (FPL) and flexor digitorum superficialis (FDS) as the revelent muscles for the acquisition of sEMG signals. Two DE-2.1 differential EMG sensors (Delsys Inc., Boston, MA) were used to collect the sEMG signals from the forearm of healthy subjects and they were placed above the corresponding muscle, respectively. A Labview virtual instrument (VI) was developed for collecting, displaying and storing the EMG signals for further processing. Fig. 3 showed the experimental facility.

During the off-line phase, the gestures were shown on the computer screen before the subjects performed, then the subjects elicited a corresponding contraction for 5 s with a comfortable force level to avoid muscle fatigue. Every gesture was repeated 10 times and there was a resting period of 6 s between each contraction. Once a gesture with ten repetitions was finished, the subjects had 5 min to relax the muscles before the next gesture. The sampling rate was 1000 Hz. During the on-line phase, a virtual hand was shown on the computer screen to display the recognition result.

Five male subjects and one female subject who are able-bodied with no neurological or muscular disorders were recruited to participate in the experiments. All the subjects signed informed consent forms.

2.2. Feature extraction and reduction

The overlapping windowing scheme was adopted to segment the raw sEMG signals. In this paper, the window length was defined as 250 ms [26] and the increment was 70 ms. The number of windows could be calculated by the following formula:

$$\text{No. of windows} = \frac{\text{data length} - \text{window size}}{\text{window increment}} + 1. \tag{1}$$

According to our previous research [22], the optimal feature set for the off-line recognition system included MAV, VAR and the 4th AR. MAV equals the mean of absolute value of sEMG signals amplitude in a window. We use $sEMG(i)\{1 \le i \le N\}$ to denote the i-th point in a sEMG window and use N to denote the length of the window. Therefore, MAV can be obtained by

$$MAV = \frac{1}{N}\sum_{i=1}^{N}|sEMG(i)|. \tag{2}$$

VAR of the sEMG signals is usually calculated as

$$VAR = \frac{1}{N-1}\sum_{i=1}^{N} sEMG(i)^2. \tag{3}$$

The 4th AR is a time series model of sEMG signals, which can be defined as

$$sEMG(i) = \mathbf{w}(i) + \sum_{k=1}^{p} a_k sEMG(i-k) \tag{4}$$

where p is the model order (p = 4), a_k are AR coefficients and $\mathbf{w}(i)$ is the residual white noise. For the on-line recognition system, the ability of robustness is essential. The on-line system should be able to resist various disturbing factors. Phinyomark et al. [13] indicated that the single robust feature was SampEn. In this paper we added the SampEn into our original feature set, which could be calculated as follows [27]:

1. For a certain sEMG window containing N points, $sEMG(i)\{1 \le i \le N\}$ formed the $N-n$ vectors:

   $$\mathbf{x}_n(j)\{1 \le j \le N-n\}, \tag{5}$$

   where $\mathbf{x}_n(j)$ was the vector of n data points from $sEMG(j)$ to $sEMG(j + n - 1)$.
2. The distance between two such vectors was defined to be:

   $$d[\mathbf{x}(j), \mathbf{x}(k)] = \max\{|sEMG(j+h) - sEMG(k+h)|, \quad 1 \le h \le N-1, j \ne k\}. \tag{6}$$

   That is the maximum difference of their corresponding scalar components.