Effects of Electrode Configuration on Pattern Recognition Based Finger Movement Classification

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Abstract. Pattern recognition (PR) based myoelectric control could provide intuitive and dexterous control of advanced prostheses. Previous studies showed that the performance of finger movements was not as good as that of wrist movements. As electrode configuration plays an important role in classification performance, this study investigated the effect of the number of electrodes and their locations on finger movement classification. An electrode selection algorithm, sequential forward searching (SFS), was applied on the high density (HD) electrode grid with 192 monopolar electrodes. With the time domain (TD) feature and linear discriminant analysis (LDA), it was found that the error rate was dramatically decreased with the number of electrodes increasing from one to ten. Under the optimized electrode configuration, the error rate could be lower than 10% with 8 electrodes, and 5% with 18 electrodes. The importance of the electrodes was measured and the results showed that the effective site for classification was mainly located around the flexor digitorum superficialis and extensor digitorum communis. This study provides the guideline for optimal placement of electrodes in finger movement recognition, and potentially provide sufficient controllability of advance prostheses with individually articulated fingers.

Keywords: Surface electromyogram · Pattern recognition · Finger movement · Prostheses · High density

1 Introduction

Surface electromyogram (sEMG) signals are electrical manifestation of muscle activity, and contains neural information about the neural signals controlling the muscles [1, 2]. This property has been exploited in many application, including myoelectric prosthesis control, where the sEMG signals collected from the remnant forearm muscles are used to control the prostheses to help the amputees restore their limb functions [3]. Conventional control scheme is based on the amplitude of sEMG signals from one pair of antagonistic muscles [4]. With this scheme, only one degree of freedom (DOF) could be activated at a time. If other DOF is desired, co-contracting the muscle group is

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needed to switch the mode. As such, this control scheme is obtrusive to the users and resulted in a high device abandonment rate [5].

Another control scheme of myoelectric prostheses is based on pattern recognition (PR) algorithms, which could provide intuitive and dexterous control of multi-function powered prostheses by creating the mapping from the user's movements to analogous prostheses functions [4, 6]. It usually adopts four to six electrodes attached around the circumference of the forearm. The major two parts of PR-based control scheme is feature extraction and classification, which extracted the property of sEMG signals and mapped the signal to the movement, respectively. The state-of-the-art algorithm is time domain (TD) feature combined with linear discriminant analysis (LDA) [7].

Previous myoelectric control studies mostly focused on wrist movements and simple grasp gestures, such as wrist flexion, wrist extension, pronation, supination, hand close and hand open [2, 8]. With only four to six electrodes attached around the forearm, the classification accuracy of these movements could reach 95% [9]. However, with the same settings, the control performance of finger movements is not as good as that of wrist movements [10]. As one of the most flexible parts of human body, finger movements are involved in most activities of our daily lives. In this study, we investigated the effect of electrode configuration on PR-based finger movement classification. High density (HD) electrode grids were used to obtain the sEMG signals of the forearm muscles. An efficient electrode selection algorithm, sequential forward searching (SFS), was applied on the signals to test the effects of the number of electrodes and their locations on classification accuracy of finger movement. The outcome would be beneficial for the socket design of the advanced prostheses.

2 Methods

2.1 Subjects

Ten healthy subjects participated in the experiments (all male and right handed, aged from 20 to 30 years old). The informed consent was obtained before the experiment and the procedures were in accordance with the Declaration of Helsinki.

2.2 Data Collection and Processing

sEMG signals were recorded using a HD electrode system (EMG USB2+, OT Bioelettronica, Italy) with 192 monopolar electrodes. The electrodes were placed on the forearm, about 3 cm distal to the elbow crease, as shown in Fig. 1. Before electrodes attachment, the skin is cleaned with alcohol pads to remove debris to increase the contact condition between the electrode and skin. The inter-electrode distance is 10 mm. The signals were filtered between 10 and 500 Hz, and digitally sampled at 2048 Hz.

Ten classes of finger movements were investigated in this study, as shown in Fig. 2. The subject was asked to sit on a chair, naturally extended their arms toward the ground. They were instructed to perform the movements with a consistent level of effort. One trial is defined as one repetition of eleven classes (ten finger movements and

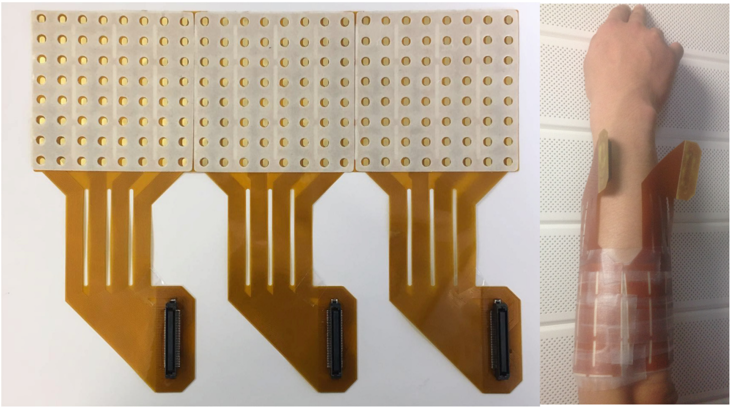

Fig. 1. HD electrode grid and its position on the subject's forearm.

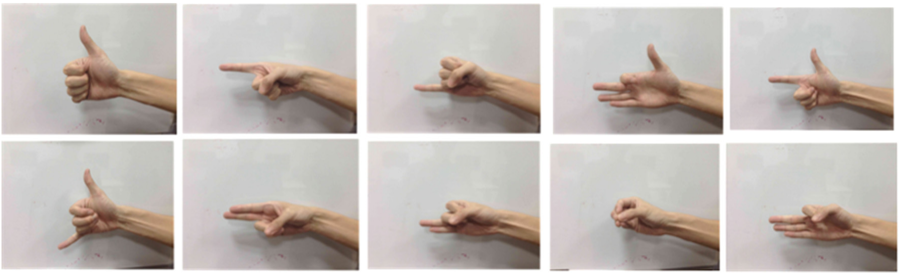

Fig. 2. Ten finger movements investigated in this study

rest), and each lasts 5 s with a 5-s rest between two classes to avoid fatigue. Sixteen trials were completed for each subject, with a 30-s rest between two trials. The entire experiment lasted about 40 min.

The sEMG signals were segmented into 200-ms analysis windows, with 150-ms overlap between two windows. TD feature set (mean absolute value, waveform length, zero crossings, and sign slope changes) [6] was extracted from each analysis window and sent to the LDA classifier.

Sequential forward searching (SFS) is a searching algorithm that selects a subset of electrodes which provides the lowest error rate with the defined number of electrodes [11]. Suppose there are a total of N electrodes, SFS calculates the error rate of one electrode for each electrode, and choose the lowest error rate as its performance of one electrode, denoted as $ER_{n(i)}$, where i is the electrode index, and $n(\cdot)$ represents the number of electrodes (equal to 1 here). Then, SFS calculates the error rate of two electrodes consist of Electrode i and the other from N-1 electrodes, and regards it as the lowest one ($ER_{n(j)}$, where $n(j) = 2$) as the performance of two electrodes. The rest N-2 error rates could be calculated in the same manner. In this study, SFS was used to calculate the error rate with the electrodes from 1 to 130. The importance of Electrode i for classification was measured by weight index (WI)

$$WI_i = \frac{\left(ER_{n(i)} - ER_{n(j)}\right)}{ER_{n(i)}} \times 100\%$$

where $ER_{n(i)}$ and $ER_{n(j)}$ represents the error rate with the number of electrodes $n(i)$ and $n(j)$ respectively, and $n(j) = n(i) - 1$. When no electrode is used, the classification error is random. So we set $ER_0 = 1/11$.

3 Results and Discussion

3.1 Effects of Number of Electrodes

The relationship between the error rate and the number of electrodes is shown in Fig. 3. The error rate decreased with the increase of the number of electrodes. The decrease rate was large when the number of electrodes increased from 1 to 6. The error rate was lower than 15% when using 6 electrodes. After that, the decrease rate turned slow and became close to zero (the error rate was stable) after the number of electrodes was increased to 25. The error rate dropped below 4% when using more than 25 electrodes.

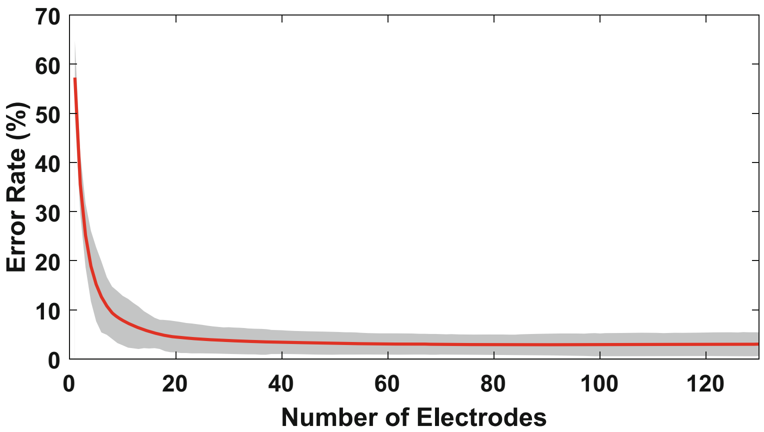

Fig. 3. Error rate of eleven movements classified with different number of the electrodes. The red line is the average value across ten subjects. The grey area represents the standard deviation. (Color figure online)

3.2 WI Distribution

The importance of the electrode in classification is measured by WI value, and their distribution is displayed in Fig. 4. The WI values of most sites were low, and high

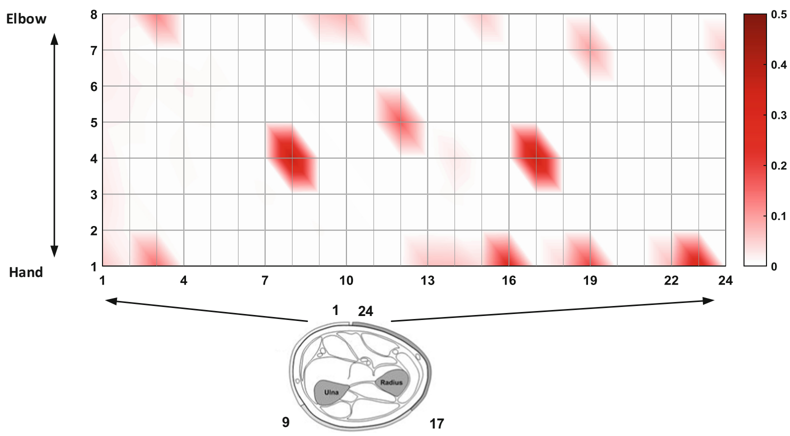

Fig. 4. Weight Index (WI) distribution of the HD electrode grid on the forearm. The vertical and horizontal axis are row and column number of the grid, respectively. The number on the section view is the column number of the grid, which corresponding to the horizontal axis.

plays an important role in finger movement classification. The most important site for finger movement classification is located around the flexor digitorum superficialis and extensor digitorum communis, which coincide with the physiological structure of the human body.

4 Conclusion

The classification of finger movements was influenced by the number of electrodes and their locations. The effect of the number of electrodes decreased with the increase of the number of electrodes, and the error rate became stable after 25 electrodes. The effective electrode location is around the flexor digitorum superficialis and extensor digitorum communis.

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