SPATIAL FILTERING FOR ROBUSTNESS OF MYOELECTRIC CONTROL ON ELECTRODE SHIFT

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ABSTRACT

Electrode shift is one of the factors that degrade the myoelectric control performance. In this study, two spatial filters, Laplacian filter (LF) and circular average filter (CAF), were separately applied on four channels of surface EMG signals, and their respective effects on the classification performance with and without electrode shift were investigated. The results on a classification task of eleven hand and wrist movements showed that CAF could significantly decreased the error rates with electrode shift, while LF significantly increased the error rates. The outcome of this study would benefit the design of the electrodes and increased the robustness of the PR-based myoelectric control.

INTRODUCTION

Pattern recognition (PR) algorithm could provide intuitive and dexterous control of multi-functional myoelectric prostheses for the users with motor deficits [1]. For the application of the PR-based control scheme on the commercial prostheses, the key problem is its robustness against the disturbances in activities of daily life (ADL) [2-5], such as arm position movement, muscle fatigue, electrode-skin contact condition change, electrode position change, etc. Among these factors, electrode position change is inevitable between donning and doffing, and would cause dramatic performance decrease in system control [6]. As such, attentions were received and multiple methods have been proposed to reduce the effects of electrode shift, ranging from the training strategy, electrode configuration to the feature extraction and classifier selection [6-8].

As the electrode position change led to the spatial changes of EMG signals, the application of the appropriate spatial filters could potentially improve the classification performance under electrode shift. Recently, some advanced spatial filters were applied on the high density (HD) electrode gird and low classification errors were achieved when electrodes shifted [9-10]. Considering the problem of practical use of the HD electrode grid in current socket systems, this study focused on the simple spatial filter operators with a small number of electrodes. Two spatial filters, Laplacian filter (LF) and circular average filter (CAF), were investigated in this study and their effects on classification performance with and without electrode shift were investigated.

METHODS

<u>Data Collection</u>

Nine able-bodied subjects (all males, from 20 to 30 years old) participated in the experiment. The informed consent was obtained before the experiment and the procedures were in accordance with the Declaration of Helsinki.

Eleven classes were investigated in this study, which were hand open, hand close, wrist flexion, wrist extension, radial flexion, ulnar flexion, pronation, supination, fine pinch, lateral prehension and rest. One run was defined as one repetition of these eleven classes, and each contraction lasted 5 s. A total of 16 runs were performed for one subject. The rest time was 5 s between two consecutive contractions and 30 s between two consecutive runs.

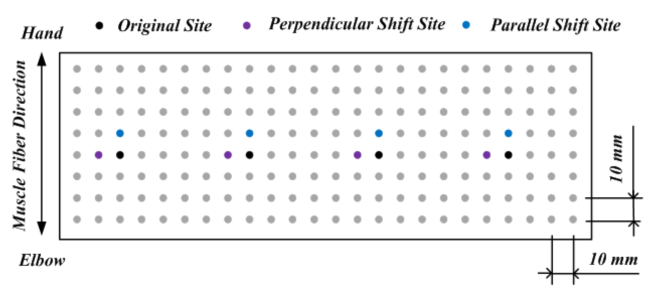

Figure 1: The original electrode site and its corresponding shift site.

A high density (HD) grid with 192 monopolar electrodes were used to collect EMG signals from the forearm. The inter-electrode distance was 10 mm and the grid was approximately 30 mm distal to the elbow crease. The signals were amplified with a commercial system (EMG USB2+, OT Bioelettronica, Italy) and sampled at 2048 Hz. As the current practical socket design would not allow for hundreds or even tens of channels, only four channels, evenly spaced around the forearm, were considered in this study (Fig. 1). Three cases were investigated, which were no shift, 10 mm shift parallel to muscle fibres, and 10 mm shift perpendicular to muscle fibres. The 10 mm shift distance was chosen for it was more likely in the daily life use situations [7].

Signal Processing

Two spatial filters common used in the image processing, Laplaician filter (LF) and circular averaging filter (CAF), were investigated in this study. LF is a high-pass spatial filter while CAF is a low-pass filter [11]. The operator of each filter is a three dimensional matrix (Table 1). The baseline (BL) is defined as the classification performance with four channels without filter. The signals of one channel are filtered by weighted summation of its own and neighbouring recordings. Suppose the filter operator matrix is S[i,j], the value of EMG signal from the channel located at row m, column n is E[m,n], the filtered signal F[m,n] is

$$F[m,n] = \sum_{i=1}^{3}\sum_{j=1}^{3} E[m-2+i, n-2+j] \times S[i,j]$$

The raw signals were segmented into 200 ms windows, with an overlap of 150 ms. Four time domain features, *i.e.* mean absolute value, zeros crossings, slope sign changes, waveform length [12], were extracted from each window. The classifier was linear discriminant analysis (LDA) [13] and the fold of cross validation was two.

Table 1: Spatial Filter Operator

Name	Matrix
Laplacian Filter (LF)	$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix}$
Circular Averaging Filter (CAF)	$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix}$

Statistical Analysis

A two-way ANOVA was conducted on the classification errors to compare the methods and shift conditions. Focused ANOVA would be performed by fixing the levels of one factor when the interaction between two main factors was significant in the full model. When significance was detected for the main factors, Tukey comparison was performed. The significance level was 0.05.

RESULTS

The classification errors of all the three methods were increased with electrode shift (Fig. 2). In all scenarios (with or without shift), the error rates of CAF, was either the smallest or one of the smallest, while LF was always the worst. The results of the two-way ANOVA revealed that there were significant interactions between the factors of methods and shift conditions. The following focused ANOVA showed that when there was no shift, the performance of CAF and BL was significantly better than that of LF, while no significant difference was detected between BL and CAF. For both shifting scenarios, the performance of CAF was significantly better than that of LF and BL, and the performance of BL was significantly better than that of LF.

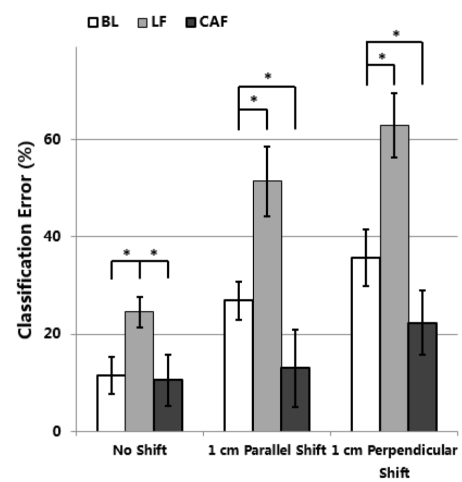

Figure 2: Classification errors of three methods, baseline (BL), Laplacian filter (LF) and circular averaging filter (CAF). The results are averaged across nine able-bodied subjects. Error bars represents the standard deviation. The star (*) represents that significant difference is detected between two corresponding methods.

DISCUSSION

This study investigated the effect of two spatial filter, LF and CAF, on the classification of eleven hand and wrist movements with and without electrode shift. Spatial filters were approved to be effective in improving myoelectric control performance [9-10]. The simplicity of the filters adopted in this study made them possible to be implemented in the real-world myoelectric prostheses control. It was observed that the classification errors after shift were greatly decreased by the application of CAF, while LF had the opposite effect (increasing error in all three cases investigated). This result is indeed expected: as CAF is a low-pass filter, it extracts information that is insensitive to the spatial variations. On the contrary, LF is high pass and extracts information sensitive to the spatial variations. As electrode shift caused changes in spatial domain, it was reasonable that the robustness of the system was increased by CAF, and decreased by LF. It was unexpected that the performance without shift was decreased by LF. The high sensitivity of LF to the noise might be the reason for this phenomenon, and it could be overcome by the combination of a low pass filter [11], such as Gaussian filter.

Only 4 channels were used in the calculation of the BL results, while 16 channels (12 neighbouring channels) were used in the calculation of the results for LF and CAF, which made the comparison biased to the advantages of the spatial filters. However, as the extra 12 channels were all located around the 4 channels with 10 mm distance, the signals they detected would be similar to each other. Therefore, there would be no big difference between the classification results they achieved.

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