Increasing the robustness against force variation in EMG motion classification by common spatial patterns

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***Abstract*—In the practical use of an electromyography (EMG) pattern-recognition based myoelectric prosthesis, the variation of force levels to do a motion would be inevitable, which will cause a change of EMG patterns. Therefore, the force variation will decay the performance of a trained classifier. In this study, the common spatial pattern (CSP) method was proposed with an attempt to improve the robustness of EMG-PR based classifier against force variation. The EMG signals were acquired from three able-bodied subjects when they were performing the motions at low, medium, and high force levels, respectively. And in the pattern recognition, CSP features were extracted from the EMG signals for motion classification. By comparing the classification accuracies between the CSP and the commonly used time-domain (TD) features, the CSP features showed a better robustness against force variation with an increment of 5.3% of the average classification accuracy. Especially, the classification accuracy of a classifier was 84.2% when tested at low force level by using CSP features, which was 18.5% higher than that of the TD features. These preliminary results suggest that using CSP features may increase the robustness of EMG-based myoelectric control.**

I. INTRODUCTION

Electromyography Pattern Recognition (EMG-PR) control method is an advanced and intelligent technique and have been investigated in many laboratories worldwide [1-4] The previous studies have reported that applying the EMG-PR method could achieve a very higher classification accuracy (95%) in identifying a number of limb movements in a well-prepared laboratory setting[5-7]. Thus the EMG-PR methods have been considered as a promising technique to provide an intuitive and dexterous control of upper-limb prosthetic devices. However, after several years of efforts, there are still many obstacles for EMG-PR based multifunctional myoelectric prostheses to be commercially available for clinical use. One of the major challenges is that the existing EMG-PR based prosthetic devices are not robust enough for real life applications [8, 9].

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The basic assumption of the EMG-PR method is that the EMG signals contain the information on user's motion intentions and are repeatable for a specific motion class [4]. However, it is practically impossible for users to produce repeatable and constant EMG signals in doing an arm movement in daily use of a myoelectric prosthesis. Generally, a motion classifier based on EMG-PR is trained with the EMG signals acquired at a certain level of force for motion execution. In the practical use, the force exerted by users may vary in different situations, which will cause the change of EMG patterns. Recently, several previous studies have been conducted to investigate the effect of force variation. Dennis et al. demonstrated that the classification performance of the commonly used time domain (TD) features was greatly affected on the force variation [10]. And Scheme et al. showed that the classification error was considerably increased 32% or even higher if a force variation ranging from 20% to 80% [6]. Obviously, the effect of force variation is an important issue in EMG-PR based prosthesis control and should be addressed.

Recently, several efforts have been made to reduce the effect of force variation on EMG-PR based motion classification. Scheme et al. and Ali et al. showed that the classification performance could be improved when using a classifier trained with data from various force levels [6, 11]. Scheme et al. further proved that using data only from the lowest and the highest force levels would also reduce the effect of force variation considerably[5]. And in our previous work, a Parallel Classification Strategy consisting of parallel classifiers created at various force levels was proposed [2]. By categorizing the input signals into the corresponding classifier, this method obtained a great improvement in motion classification. However, acquiring the data from various force level to train a classifier is cumbersome in clinical prosthesis application.

In order to provide a more feasible approach to reduce the effect of force variation on sEMG-PR based motion classification, common spatial patterns (CSP) [8, 12], a widely used feature extraction method for electroencephalogram (EEG) signal classification was adopted in this study. And the classification performances were compared between the CSP and four commonly used TD features to show the good robustness of the CSP features against force variations.

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Figure 1. Placement of electrodes for EMG data recording.

II. METHODS

A. Subjects

Three able-bodied subjects were recruited in this pilot study. The age of the subjects ranged from 23 to 26 years. The experimental protocols were approved by the Shenzhen Institutes of Advanced Technology, Chinese Academy of Sciences. And all subjects provided permission for publication of photographs for scientific and educational purposes.

B. Data acquisition and analysis

A high-density EMG system (REFA 128, TMS international, the Netherlands) was used to record EMG data. All channels of EMG signals were passed through a band-pass filter with cut-off frequencies of 10 and 500 Hz, and the sampling rate was 1024Hz. For each subject, 32 electrodes were evenly positioned in a 4×8 grid around the dominanted forearm, as shown in Fig.1.

Five motion classes of hand open (HO), hand close (HC), wrist pronation (WP), and wrist supination (WS), and no-movement (NM), were designated in this study. For each subject, the experiment comprised three sessions with different force levels:

1) Medium force session:
Each subject was asked to perform a contraction with moderate effort that is naturally produced and is about 50% of the Maximum Voluntary Contraction (MVC).

2) Low force session:
A force level that is lower than the usual moderate level was exerted by subjects, and it is about 20% of the MVC.

3) High force session:
Subjects were instructed to produce a force level that is higher than the moderate level and is about 80% of the MVC.

In each session, subjects were asked to perform a motion class at a designated force level and hold it for 5 s, by following a prepared video prompt. Each motion class was repeated 10 times with a rest of 5 s in between. And there is a 3-min rest between two sessions to avoid muscle fatigue.

C. Common spatial patterns

CSP is a supervised algorithm to obtain linear spatial filters that could maximize the variance of one class and minimize the variance of another class simultaneously. This algorithm has been widely used in classification of motor imaginary EEG data for brain computer interfaces due to it could maximally separate different imagination classes based on their variances [8].

The raw EMG signals of motion class *i* and *j* were denoted as X_i, and X_j with a dimension of m×n, where m is the number of channels and n is the number of samples per channel. According to the purpose of CSP, it was to find the coefficients w of the spatial filter $y = w^T X$, which maximized the variance of class *i* and minimized the variance of class *j*. This optimization problem could be formulated as follows:

$$w = \arg\max_{w} \frac{w^T \sum_i w}{w^T \sum_j w} \tag{1}$$

Where $\sum_i = 1/(n-1) * X_i * X_i^T$, and $\sum_j = 1/(n-1) * X_j * X_j^T$ were the covariance matrix of class *i* and *j*.

The solution can be obtained by finding the matrix w that simultaneously diagonalized both $\sum_i$ and $\sum_j$, as presented in (2) and (3).

$$W \sum_i W^T = D_i \tag{2}$$

$$W \sum_j W^T = D_j \tag{3}$$

$$D_i + D_j = I \tag{4}$$

The row vectors of W were the *m* spatial filters. By applying the filter to the raw sEMG signals, we got the output signal Y = W * X, which were called components. Based on the constraint (4), the component with the highest eigenvalue for class X_i has automatically the lowest eigenvalue for class X_j and is the solution of (1). In this study, the two eigenvectors corresponding to the highest and lowest eigenvalues for class D_i were selected as the components for a spatial filter.

Since there were five motion classes in this study, the one versus rest (OvR) scheme [12] was used to extend the two-class CSP into multiclass CSP. In OvR scheme, each filter was designed to maximize the variance of one motion class and minimize the average of the variances of all other classes. Thus, there were N filters for N classes, and the features of the selected components from each filter were concatenated into one feature vector.

C. Feature extraction and visualization

The sEMG signal analysis was performed offline with Matlab (*The Mathwork Inc.*). To investigate the effect of force variation on the classification performance, first half of the EMG signals recorded at medium force level was used as the training set, while the other half of the medium force level recordings, and the low and high force level EMG recordings were used as the testing set. And then the signal recordings were segmented into a series of 150-ms analysis windows with an increment of 100 ms. For each analysis window, the variances of the selected CSP components were calculated as features for motion classification. And for comparison purpose, four commonly used TD features of mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and number of slope sign changes (SSC) were also extracted from each analysis window [4, 7, 13, 14].

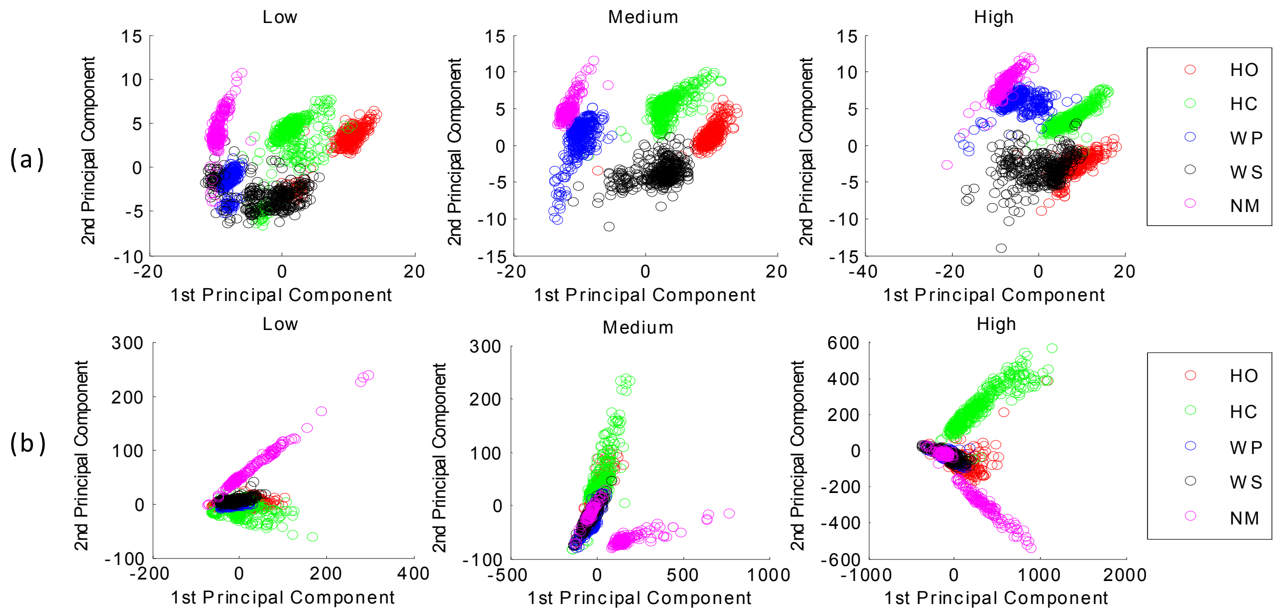

Figure 2. Feature space of the five motion classes at different force levels. (a) CSP features, and (b) the four TD features.

To investigate the feature space shifts between different force levels, scatter plots of the CSP and TD features were visualized in two-dimensional space by using the principal component analysis as presented in [15].

D. Classification

The Linear Discriminant Analysis (LDA) algorithm [7] which was widely used in EMG-PR based motion classification was adopted in this study. The performances achieved by using CSP and TD features were assessed by classification accuracy of a trained LDA classifier in (5).

$$\text{classification accuracy}=\frac{\text{Number of correctly classified samples}}{\text{Total number of testing samples}}\times 100\% \qquad (5)$$

III. Results

A. Comparison of CSP and TD feature spaces

Fig.2 showed the CSP and TD feature spaces of the five motion classes at low, medium, and high force levels respectively. It can be observed that there were shifts in the feature spaces at low and high force levels relative to the space at medium force level for both CSP and TD features. From the comparison of Fig.2 (a) and (b), it can be seen that the class separability of CSP features were much better than those of the TD features at all the three force levels (low, medium, and high). And the CSP feature spaces of the five motion classes had a better consistency at the three different force levels compared to the TD feature spaces, especially for the HO and HC motions which appeared an obvious shift between the low force level and the medium/high force level in TD feature space.

B. Comparison of Classification performance

The comparison of classification performance between the CSP and TD fetures was shown in Fig. 3. We can see from Fig. 3 that the average classification accuracy across the three force levels (low, medium, and high) of CSP features was 91.6%, which was 5.3% higher than that of the TD features. Among the three force levels, the trained classifier achieved the best classification performance of about 98% when tested at medium force level. And the performance was reduced when the classifier was tested at the low and high force levels. Especially at the low force level, the classification accuracy of the TD features was only 65.7%. However, when using the

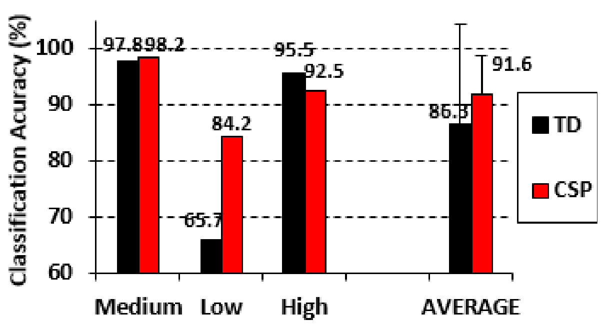

Figure 3. Classification performance of the CSP and TD features for different force levels.

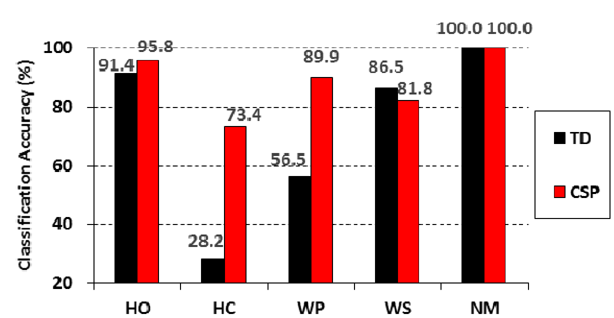

Figure 4. Classification performance of the CSP and TD features for the five motion classes at low force level.

CSP features, the classification accuracy was 84.2%, which was about 18.5% higher than that of the TD features.

Fig. 4 showed the classification performance comparison of each motion class between the CSP and TD features at low force level. It can be observed that for the HC and WP motion classes, the classification accuracies obtained by the TD features were 28.2% and 56.5%, respectively, which were greatly lower than those of other motion classes and far from satisfaction in prosthesis control. By using the CSP features, the classification accuracies of HC and WP were 73.4% and 89.9%, which were 45.2% and 33.4% higher than those of the TD features, respectively.

IV. Discussion

The four TD features of mean absolute value (MAV), waveform length (WL), zero crossing (ZC), and number of slope sign changes (SSC), were commonly used in EMG-PR based motion classification. However, many previous studies reported that the motion classification accuracy achieved by using these TD features was usually influenced by force variation. The possible reason may be that the TD features were susceptible to force variations, e.g. the feature of MAV, which varied significantly among different force levels [2]. In this study, the feature space shift between the low, medium, and high force levels were investigated. From Figure2 (b), it can be clearly seen that the TD feature space of the five motion classes had an apparent shift between the three different force levels. Especially, the feature space was shifted severely at the low force level. This finding may explain the conclusion of some previous studies that the classification error rates was high when testing the classifier at the low force level [11, 16].

To reduce the effect of force variation, we proposed to use CSP features instead of the four TD features for EMG-PR based motion classification. Fromm Fig.2 (a), it can be observed that the CSP feature spaces of the three different force levels were similar to each other, achieving a better class separability in two-dimensional feature space compared with the TD features. Therefore, the classifier trained with the CSP features had the correspondingly better classification performance across different force levels, as shown in Fig.3. Especially for the low force level, the classification accuracy was increased from 65.7% to 84.2% by using the CSP features. And from Fig.4, it can be seen that the classification accuracies of HC and WP were only 28.2% and 56.5% when using TD features, which were greatly affected by force variation. However, when using the CSP features, the classification accuracies of HC and WP were 73.4% and 89.9%, which were 45.2% and 33.4% higher than those of the TD features. Thus these preliminary results suggest that the CSP would be promising in enhancing the robustness of EMG-PR based motion classification against force variation.

It should be noted that only three able-bodied subjects were recruited in this pilot study. In future work, more subjects including amputees with different amputation levels would be recruited to evaluate the feasibility of the CSP features in EMG-PR based motion classification. And some quantitative indicators should also be used to evaluate the feature space shift of different force levels.

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