Adaptive Pattern Recognition of Myoelectric Signal towards Practical Multifunctional Prosthesis Control

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Abstract. Towards the real-world application of multifunctional prostheses based on electromyography (EMG) signal, an unsupervised adaptive myoelectric control approach was presented in order to improve the long-time classification performance of EMG pattern recognition. The widely-used linear discriminant analysis (LDA) was improved to three new different classifiers separately termed as linear discriminant analysis with single pattern updating (SPLDA), linear discriminant analysis with multiple patterns updating (MPLDA), and linear discriminant analysis with selected data updating (SDLDA). The experimental result showed that the three new classifiers significantly outperformed the original version. MPLDA and SDLDA provided two different methods to decrease the influence of misclassification and got lower classification error rates than SPLDA. Strategies to decrease the influence of misclassification are the key to the application of unsupervised myoelectric control in the future.

Keywords: EMG, prosthesis, pattern recognition, adaptation, LDA.

1 Introduction

Surface electromyography (EMG) signal, which is noninvasive and contains rich information associated with the muscle electrical activities, is considered to be an important input for the control of electrically powered prostheses [1]. To increase the number of functions of prostheses, much attention has been drawn to a pattern recognition based approach to the myoelectric control in last two decades and some promising results have been achieved [2-4].

By learning the nature of muscle contraction patterns for the intended movements of a specific user, pattern recognition can provide the advantage of recognizing the subtleties of the user's muscular activity at a particular instance in time. However, it does not accommodate changes in the EMG patterns over time and the good performance cannot maintain for a long time because of the EMG variations, due to electrodes condition, muscle fatigue, sweating and so on [5]. This problem has become an obstacle for the commercialization of advanced myoelectric controlled prostheses developed in laboratory environment.

The conventional pattern recognition method is accomplished in two parts, training and testing. The parameters acquired at the training contain limited information, and

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they cannot be representative to the data of the whole temporal span in application period including testing step. It is the main cause to the above remarked problem. Therefore, how to make the parameters more representative to the EMG signal is the key to improve the long-time performance.

In this paper, we exploited EMG information in the testing part, and an unsupervised adaptive myoelectric control approach was presented to improve the long-time classification performance of EMG pattern recognition. As the Linear Discriminant Analysis (LDA) is a computationally efficient algorithm with similar performance to more complex algorithms [4], it was improved with this approach and the new classifier, linear discriminant analysis with single pattern updating (SPLDA), was constructed. The experimental results showed a significant improvement in long time performance, compared with the original version. However, the existence of misclassification would bring adverse effect on the classifier and lead to a bad result. To reduce its influence, two different methods were proposed, which were separately from the aspects of data selection and multiple patterns updating. The corresponding classifiers were called linear discriminant analysis with multiple patterns updating (MPLDA), and linear discriminant analysis with selected data updating (SDLDA). The performance of MPLDA and SDLDA would compare with SPLDA, and they could be used in the control of multifunctional prostheses.

2 Methods

2.1 Overview

The traditional myoelectric control based on pattern recognition generally contains segmentation, feature extraction, and classification [6]. The decision streams are finally generated for the motion controller. Unlike the traditional method, a feedback to the classifier is added in the unsupervised adaptive myoelectric control and it is illustrated in Figure. 1. Samples tagged with the results of the classifier were used to retrain the classifier to make it adaptive to the changes of EMG signal over time.

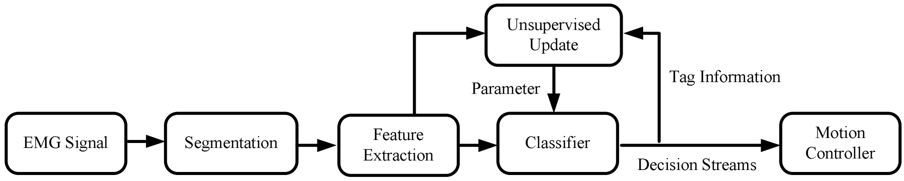

Fig. 1. Block diagram of the unsupervised adaptive myoelectric control scheme

2.2 Linear Discriminant Analysis (LDA)

A widely-used classification algorithm in EMG research is the LDA. A linear classifier, in general, tries to establish a hyperplane separating the signal space into individual subspaces for all classes [7]. It can be found in literature [8] that the formulae of LDA based on a multivariate normal distribution to each group, with a pooled estimate of covariance.

2.3 Adaptive Linear Discriminant Analysis

The main parameters of the LDA classifier are the mean vector of each class and the pooled covariance matrix. Suppose that there are N patterns used for training the classifier, and the new-coming testing EMG feature patterns are acquired as x_{N+1}, x_{N+2}, x_{N+3}, cet. Let the pattern x_{N+1} be z and labeled as class k by the original classifier. The updated mean vector $\tilde{\mu}_k$ for class k is

$$\tilde{\mu}_k = \frac{n_k * \mu_k + z}{n_k + 1}, \tag{1}$$

where n_k is the number of future patterns for class k, and μ_k is the original mean vector.

The pooled covariance matrix $\tilde{\Sigma}_W$ is updated by

$$\tilde{\Sigma}_W = \frac{N}{N+1}\Sigma_w + \frac{1}{N+1} * \frac{n_k}{n_k+1}(z-\mu_k)(z-\mu_k)^T, \tag{2}$$

where Σ_w is the original pooled covariance matrix.

2.4 Decrease of Influence of Misclassification

There are different strategies to update the classifier. The most common one is to recalculate the parameters when one single pattern is generated, and we call it adaptive LDA with single pattern updating (SPLDA). However, it is known that the classification error is inevitable and patterns with wrong tags may damage the classifier during the process of feedback and lead to a bad result. To reduce its influence, we propose two different methods from aspects of data selection and multiple patterns updating.

An entropy function is introduced to test the confidence of classification and only the data that is of high confidence will be used to update the classifier. That is intended to reduce the number of wrong-tagged pattern and decrease its adverse influence. We call it adaptive LDA with selected data updating (SDLDA).

The entropy function used for data selection in SDLDA is [9]

$$E(n) = -\sum_{k=1}^{K} p_k(n) ln\,(p_k(n)), \tag{3}$$

where K is the number of classes to be considered and $p_k(n)$ is the probability of class k in future pattern n defined as follows,

$$p_k(n) = \frac{1/d_k(n)}{\sum_{k=1}^{C} 1/d_k(n)}, \tag{4}$$

$$d_k(n) = (z - \mu_k)^T \, \Sigma_w (z - \mu_k), \tag{5}$$

Another way is to use more than one pattern to update the classifier. In SPLDA, if one pattern is attached with a wrong label, its influence will be immediately reflected on the next pattern's calculation. It may lead to accumulative error and impair the classifier. However, if we decrease the frequency of updating and update the classifier after more than one pattern is calculated. Then the right-tagged pattern will weaken the influence of the wrong-tagged and reduce the accumulative error of the classifier. In this way, the influence of misclassification is reduced. It is called adaptive LDA with multiple patterns updating (MPLDA).

Therefore, three adaptive LDA classifiers were developed, which were separately called SPLDA, SDLDA, and MPLDA. MPLDA and SDLDA are better than SPLDA theoretically.

2.5 EMG Data Acquisition

The data were collected from three able-bodied subjects with four bipolar electrodes placed on palmaris longus, flexor carpi ulnaris, flexor digitorum supercifialis, and extensor digitorum. The motion classes were consisted of wrist flexion/extension, forearm pronation/supination, hand open/close, radial flexion, ulnar flexion and resting (no motion). Motions are shown in Figure. 2. Signals were pre-amplified and filtered using a commercial myoelectric system (Delsys Inc., Trigno^{TM} Wireless System, 20-450 Hz band pass filter) and recorded at a sampling rate of 2 kHz. Four time-domain EMG features (mean absolute value, waveform length, zero crossings, and slope changes) [3] extracted from 200 ms windows of filtered EMG from each channel resulted in a 16-element feature vector. The feature vector was calculated at 25 ms intervals (175 ms of overlapping data per window).

A single experimental trial is defined as follows. Subjects perform each of the nine contraction classes for 5 seconds with a 5-second rest between contractions. For each hour, five consecutive trials were performed and the whole temporal span of the experiment for each subject was 7 hours (40 trials of data were collected). The first five trials were assigned as a training set and the next thirty-five trials as a testing set.

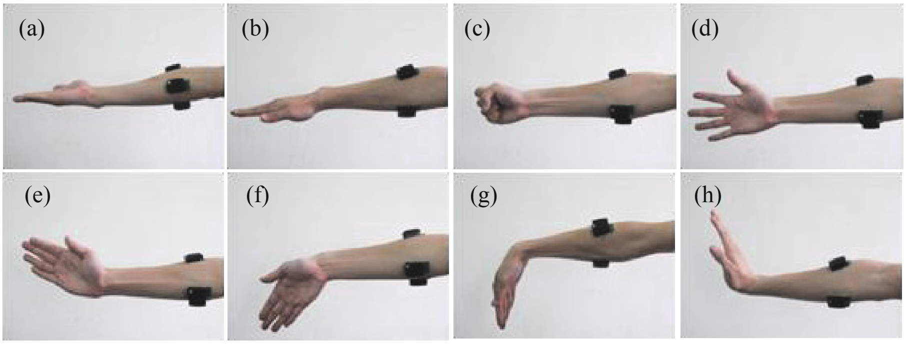

Fig. 2. Photo of different types of motions. (a) Forearm pronation. (b) Forearm supination. (c) Hand close. (d) Hand open. (e) Radial flexion. (f) Ulnar flexion. (g) Wrist flexion. (h) Wrist extension.

3 Results and Discussion

To compare the performance of different types of classifiers, the classification error rate was used as a measure, which was defined as

$$\frac{\text{Number of incorrectly classified samples}}{\text{Total number of testing samples}} \times 100\ (\%).$$

The average classification error rate of different classifiers for each subject is listed in Table. 1, and the best performance for each subject is highlighted in bold.

Table 1. Average classification error rate of different classifiers

	Error Rate (%)			
Subject	LDA	SPLDA	MPLDA	SDLDA
S1	11.01	5.49	3.24	**2.68**
S2	20.15	11.55	**8.44**	8.81
S3	29.93	22.52	19.67	**19.58**
mean	20.36	13.19	10.45	10.36

From this table, it can be seen that the performance of each subject was different for a certain classify. The average classification error rate across subjects of LDA is 20.36%, whereas SPLDA, MPLDA and SDLDA are 13.19%, 10.45%, 10.36%, respectively. It can be concluded that SPLDA, MPLDA and SDLDA significantly outperform LDA. In addition, the performance of SPLDA is approximately the same as MPLDA, which is superior to LDA.

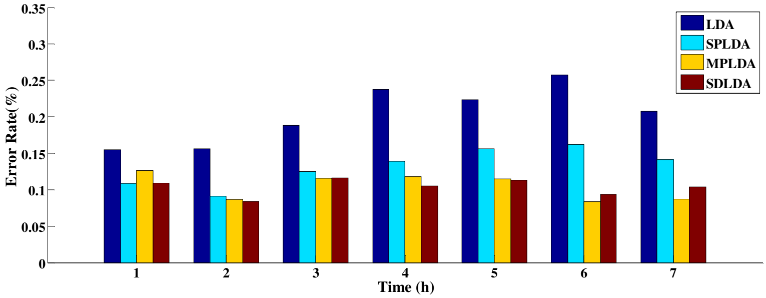

Fig. 3. Classification error rate of different classifiers. Result is averaged across all subjects.

The error rate of different classifiers over time is shown in Figure. 3. A one-way Analysis of Variance (ANOVA) was applied to analyze the classifier factor. By analyzing the performance of LDA and SPLDA, it is showed that pattern updating significantly decreases the error rate ($p < 0.01$). Meanwhile, by analyzing the results of SPLDA, MPLDA and SPLDA, SDLDA, it can be concluded that decrease of influence of misclassification has the same effect ($p < 0.05$) as pattern updating.

To determine the quality of EMG signal, the concept of minimum error was introduced [5]. It was defined as the classification error rate which was used for assessing the performance of a classifier trained and tested by the same data set. Of the three subjects, the quality of signal of subject 1 was the best and subject 3 was the worst. The classification error rate over time for S1 and S3 was shown in Figure. 4.

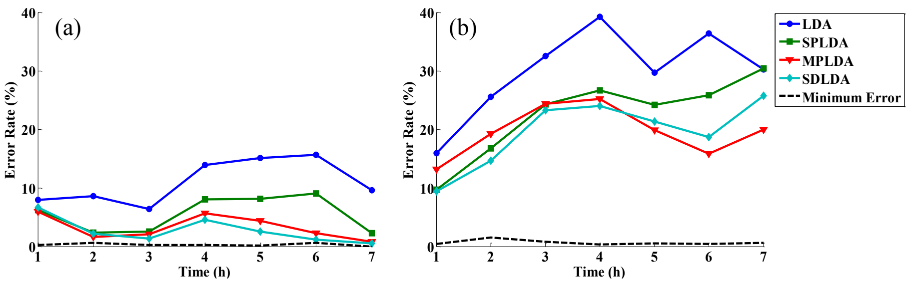

Fig. 4. Classification error rate over time. (a) Subject 1, which has the best performance. (b) Subject 3, which has the worst performance.

It can be seen that the classification error of LDA increased over time, which was caused by the variations of EMG signal. For the signal with low minimum error, the performance of SPLDA was similar to MPLDA and SDLDA. However, it was quite different from the signal of high minimum error. The different performance of SPLDA was caused by the feedback of wrong tagged samples. With the signal of high quality, the classification error was low and most of samples were right tagged. So the classifier can adapt to the changes of signal and produce better results. On the contrary, with the signal of low quality, the classification error was high and most of samples were wrong tagged. The classifier may be impaired and the results were bad. So it was necessary to decrease the influence of misclassification.

MPLDA and SDLDA provided two ways to reduce the influence of misclassification. SDLDA was slightly better than MPLDA from the aspect of classification error. However, MPLDA outperformed SDLDA during hour 5-7 in Figure. 4 (b). The update rate of SDLDA was slow for the low-quality signal, of which data with high confidence was not much, while the update rate of MPLDA was constant. As the time went by, SDLDA could not follow the trend of changes of EMG signal as well as MPLDA. So we recommended SDLDA for the high-quality signal, while MPLDA for the low-quality.

It can be inferred that supervised adaptive myoelectric control approach can achieve better results than unsupervised. However, it will increase the burden of users of prostheses and is impractical in the real world. So towards the application of prostheses in the real world, unsupervised adaptive myoelectric approach is the mainstream. SDLDA and MPLDA present two different ways to degrade the influence of misclassification. However, both of them have a coeffiecent to adjust and may not be easy enough to be applied in the real world. So further study should be done to develop a new method that is convenient and easy to use in the unsupervised myoelectric control.

4 Conclusions

The long-time performance of EMG pattern recognition is an important issue in the research of EMG controlled prostheses. Various supervised adaptation methods have been reported to overcome this problem. However, in practical application, the actual intention of the subject is not always known to the system, and unsupervised adaptation methods are needed. In this paper, the preliminary study of the unsupervised adaptive myoelectric control was presented. A new classifier derived from LDA was constructed and achieved a better performance than the original one in the following experiment. This confirms the effectiveness of our method. Different from supervised method, misclassification exists in unsupervised method, and it may cause big problems for the practical application of unsupervised myoelectric control. So two different strategies, data selection and multiple patterns updating, were proposed to reduce the influence of misclassification, and the performance of the classifiers was improved further. Towards the real-world application, our future work will focus on the method to eliminate the misclassification influence and improve the online performance of the long-time adaptive myoelectric control.

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