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An Adaptation Strategy of Using LDA Classifier for EMG Pattern Recognition

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Abstract—**The time-varying character of myoelectric signal usually causes a low classification accuracy in traditional supervised pattern recognition method. In this work, an unsupervised adaptation strategy of linear discriminant analysis (ALDA) based on probability weighting and cycle substitution was suggested in order to improve the performance of electromyography (EMG)-based motion classification in multifunctional myoelectric prostheses control in changing environment. The adaptation procedure was firstly introduced, and then the proposed ALDA classifier was trained and tested with surface EMG recordings related to multiple motion patterns. The accuracies of the ALDA classifier and traditional LDA classifier were compared when the EMG recordings were added with different degrees of noise. The experimental results showed that compared to the LDA method, the suggested ALDA method had a better performance in improving the classification accuracy of sEMG pattern recognition, in both stable situation and noise added situation.**

I. Introduction

Surface electromyography (sEMG) signals, which contain a large amount of neural information related to limb movements, are widely used as control signals for motion classification in the system of motorized myoelectric prostheses [1-3]. In order to control multifunctional prostheses properly, decoding multiple patterns of hand/wrist-movement from sEMG signals with desirable accuracy rate is required and expected.

The motion prediction based on sEMG pattern recognition is comprised of two components: feature extraction and motion classification. Several different classification algorithms such as linear discriminant analysis (LDA) [4], fuzzy logic [5], artificial neural networks (ANN) [6,7] and support vector machine (SVM) [8] have been used in most of the previous studies to assess their feasibility and performance in classifying a number of motion classes. It has been shown in previous work [3,6,8] that without a compromise of classification accuracy, the LDA classifier is much simpler to implement and much faster to train in comparison to other types of classifiers. However, the performance of a LDA classifier in identifying movements is still limited in long time control of multifunctional prostheses due to the changes of EMG signals over time [9,10].

In traditional sEMG pattern recognition, the parameters of a LDA classifier are achieved by training a group of pre-recorded sEMG signals [1-7]. Thus a trained classifier in a static status may not adapt to time-varying signals. On the other hand, many researches have indicated that sEMG signals recorded from skin surface are time-varying due to sweating, electrode position shift, muscle fatigue, and more [9,11-13], which may change features of the recorded sEMG signals and decay the accuracy of a trained classifier. Therefore, a classifier with environmental adaptability should be critical for pattern recognition of myoelectric prosthetic hands.

In order to adapt to the time-varying characteristic of sEMG signals, unsupervised adaptive linear discriminant analysis (ALDA) classifiers have been investigated [9,10,13,14], in which adaptation strategies were incorporated for updating the parameters of LDA classifier to improve the classification performance accordingly. The primary advantage of the ALDA method is that updating strategy makes the classifier be self-adaptive, resulting in enhancing the performance of prostheses control system when sEMG recordings are changed over time. In this paper, an ALDA classifier based on probability weighting and cycle substitution was proposed and its performance in classifying different arm movements was investigated for control of multifunctional myoelectric prostheses. The datasets used for testing the performance of the classifier and the adaptive strategy based on probability weighting and cycle substitution were firstly described, and then the improvement of the proposed method was demonstrated by several datasets.

II. Materials and Methods

A. EMG Signal Acquisition

sEMG signals were recorded from five able-bodied subjects (three males and two females, aged from 22 to 46 years) when they were performing a wrist or hand movement following a visual instruction without feedback. Twelve self-adhesive bipolar electrodes with a circular contact surface diameter of 1.25 cm and a center-to-center distance of 2 cm were used for sEMG recordings, and were placed on the proximal forearm, the wrist, and the hand on the dominated arms of subjects, respectively. A large circular electrode was placed on the elbow of the tested arm as the ground. The

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protocol of this study was approved by Shenzhen Institutes of Advanced Technology, Chinese Academy of Science. All subjects gave written informed consent.

Ten motion classes, four wrist motions (Flexion and Extension, Pronation and Supination), and six hand motions (Hand Open, Chuck Grip, Key Grip, Power Grip, Fine Pinch Grip, and Tool Grip), as shown in Fig. 1, were involved in the study. sEMG signals were amplified and band-pass filtered (5-400 Hz), and then sampled at a frequency of 1 kHz and acquired with a custom data acquisition and processing system. Pattern recognition was performed on the sEMG data which were segmented into a series of 150 ms analysis windows. Four time-domain features (Mean Absolute Value, Willison Amplitude, Zero Crossing, and Root Mean Square) were extracted from each analysis window as a representation of the signals, and were used in classifier to recognize the intended movement patterns.

Fig.1. Ten classes of arm- and hand-movements plus a "no movement" performed in this work.

B. Linear Discriminant Analysis (LDA)

Linear discriminant analysis (LDA) classifier has been widely used in sEMG pattern recognition for prostheses control [1, 14]. It is based on the Bayes classification rule, where for a given vector *x*, assign it to the class c_k when the following inequality is satisfied:

$$p(c_k|x) > p(c_j|x) \text{ for all } k \neq j \tag{1}$$

These posterior probabilities can not be directly measured, but can be derived from estimates of the priori probabilities and the class distribution according to the Bayes formula:

$$p(c_k|x) = \frac{p(c_k)\,p(x|c_k)}{p(x)} \tag{2}$$

where $p(x|c_k)$ is the probability density function for the vector within *k* class, $p(c_k)$ is the prior probability for class *k* and usually assumed to be equal for all classes, $p(x)$ is the probability density function of the input space and is also a constant over all the classes. Then the decision rule referred in (1) is simplified to:

$$p(x \mid c_k) > p(x|c_j) \text{ for all } k \neq j \tag{3}$$

In the implementation of LDA classifier, the probability density functions for all the classes are assumed to follow a multivariate Gaussian distribution:

$$p(x|c_k) = \frac{1}{\sqrt{(2\pi)^f \det(C)}} \exp(-\frac{1}{2}(x-\mu_k)^T C^{-1}(x-\mu_k)) \tag{4}$$

where *x* is the vector to be classified, f is the dimension of the vector, C is the common covariance matrix of all the classes, and μ_k is the mean value of class *k*.

For a given training dataset, the parameters μ_k and C are fixed and the LDA classifier is static. Thus the LDA classifier would be difficult to keep the classification accuracy unchanged when the EMG recordings in doing a movement is changed over time.

C. Adaptive Linear Discriminant Analysis (ALDA) Based on Probability Weighting and Cycle Substitution

In order to get a decoding algorithm that was able to track the change of sEMG signal, adaptive mechanism was added to the LDA method, including cycle substitution of train dataset and parameters adjustment according to probability weighting which was similar with the weighting regression method in data mining.

The cycle substitution step could be summarized as that for every new feature vector and its estimated probabilities, a decision was firstly made by the classifier, and then an old feature vector belonging to the same class in the training set was replaced. The operation mode kept the training dataset updating constantly and ensured that it could track the change of the signal. It was noted that not all of the data in the training dataset were included in the cycle substitution process. Only one part of the training set was carried through the process, and another part would never be updated in order to maintain the stability of the classifier.

After a cycle substitution process, the new classifier parameters would be computed by Eqs.(5) and (6). This was referred as probability weighting step. The adjustment weight of the mean vector and covariance matrix C for each class was determined by probability distribution of the feature vectors in each type. The fixed part of training dataset was obtained under supervised condition and their class label was known. The probability of correct class was 1, and that of other classes were 0. The cycle part of the training dataset participated in the parameters adjustment according to the class posterior probabilities calculated before making the decision. The parameters μ_k and C is redefined as [14]:

$$\mu_k = \frac{1}{p(c_k)N}\sum_{i=1}^{N} p(c_k|x_i)x_i = \frac{1}{\sum_{i=1}^{N} p(c_k|x_i)}\sum_{i=1}^{N} p(c_k|x_i)x_i \tag{5}$$

$$C = \frac{1}{N-1}\sum_{k=1}^{K}\sum_{i=1}^{N} p(c_k|x_i)(x_i-\mu_k)(x_i-\mu_k)^T \tag{6}$$

The whole process of the ALDA method can be described by the flow chart (Fig. 2):

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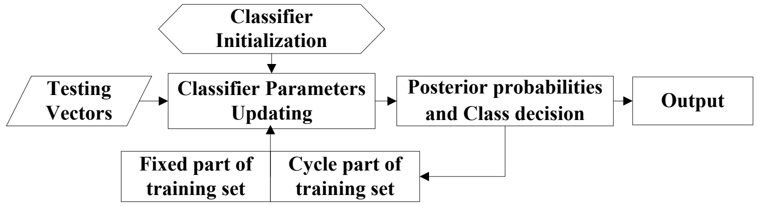

Fig.2. The flow chart of the ALDA process

D.Classifier Performance

When the same dataset was used as test dataset as well as train dataset , a more perfect classification result would be obtained. For each subject in the experiment, the dataset was divided into two parts. The first part was used to train a LDA classifier and the second part was used to test the motion classification performance of the proposed ALDA method and the static LDA. In order to test the adaptation ability of the two classifiers, varying degrees of random noise was added to the testing datasets while the training datasets kept unchanged. The noise level was determined by the product of the standard deviation of the test vectors and a factor as follows:

$$Noise = std(test\ vector) \times factor \tag{7}$$

The performance of the classifier in identifying movement type was measured by the classification accuracy and raising rate of classification accuracy, which were defined as below respectively:

$$\frac{Number\ of\ correctly\ classified\ samples}{Total\ number\ of\ testing\ samples} \times 100\% \tag{8}$$

$$Raisin g\ Rate = \frac{\text{ALDA Accuarcy-LDA Accuarcy}}{\text{LDA Accuarcy}} \times 100\% \tag{9}$$

III. RESULTS

A. Classification Performance versus Cycle Substitution Proportion

Table I summarizes the classification accuracy versus cycle substitution proportion for different noise level (NL) being added into the testing dataset in one subject. Both LDA and ALDA classifiers showed a good performance (classification accuracy higher than 95%) when the test data were not contaminated by noise. A better performance was achieved by the ALDA classifier (classification accuracy of 65.66%~90.74%versus different cycle substitution) than the LDA classifier (classification accuracy of only 44.95%) when noise (with 100% level) was added into the testing data. Overall, the classification accuracy trended to decrease with the increasing noise levels for both two classifiers. However, no matter how much the cycle substitution proportion (CP) was, the ALDA classifier always had a higher classification accuracy than the LDA classifier .

Fig.3 shows the raising rate of classification accuracy as a function of the cycle substitution proportion for different noise levels. It can be seen from Fig. 3 that the selection of substitution proportion could influence the performance of the ALDA classifier. A substitution proportion from 40% to 70% could provide a good classification performance. As a sequence, in the following study a cycle substitution of 50% was selected for our ALDA classifier.

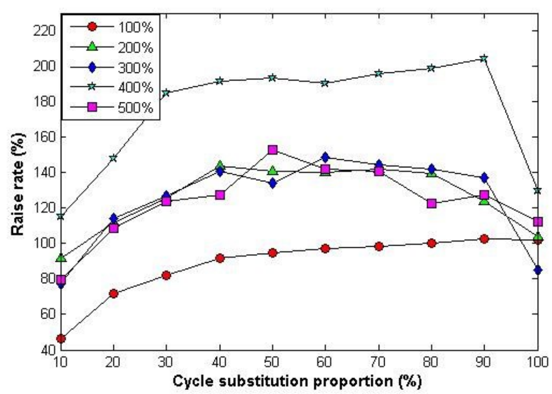

Fig.3. The raising rate of classification accuracy versus cycle substitution proportion for different noise level.

B. Classification Accuracy in Different Subjects

EMG recordings from five subjects were used to compare the performance of LDA and ALDA classifiers. Fig.4 shows the classification accuracy of both classifiers for each subject at noise levels of 50% and 200%, respectively. Obviously, compared to LDA classifier, ALDA classifier showed a better performance for all the subjects both in the two noise levels, especially for higher level noise in testing EMG signals.

TABLE I CLASSIFICATION ACCURACY OVER SIX NOISE LEVEL AT DIFFERENT CYCLE SUBSTITUTION PROPORTION (%)

	(LDA) 0%	**CP: 10%**	**CP: 20%**	**CP: 30%**	**CP: 40%**	**CP: 50%**	**CP: 60%**	**CP: 70%**	**CP: 80%**	**CP: 90%**	**CP: 100%**
NL: 0%	95.12	95.45	97.64	99.33	98.99	99.83	99.83	99.83	99.83	100.00	100.00
NL: 100%	44.95	65.66	77.27	81.82	86.20	87.54	88.55	89.06	89.90	91.08	90.74
NL: 200%	26.43	50.67	55.89	59.60	64.48	63.64	63.47	63.97	63.30	59.09	53.87
NL: 300%	19.36	34.34	41.41	43.94	46.63	45.29	48.15	47.31	46.80	45.96	35.86
NL: 400%	12.29	26.43	30.47	35.02	35.86	36.03	35.69	36.36	36.70	37.37	28.28
NL: 500%	13.97	25.08	29.12	31.31	31.82	35.35	33.84	33.67	31.14	31.82	29.63

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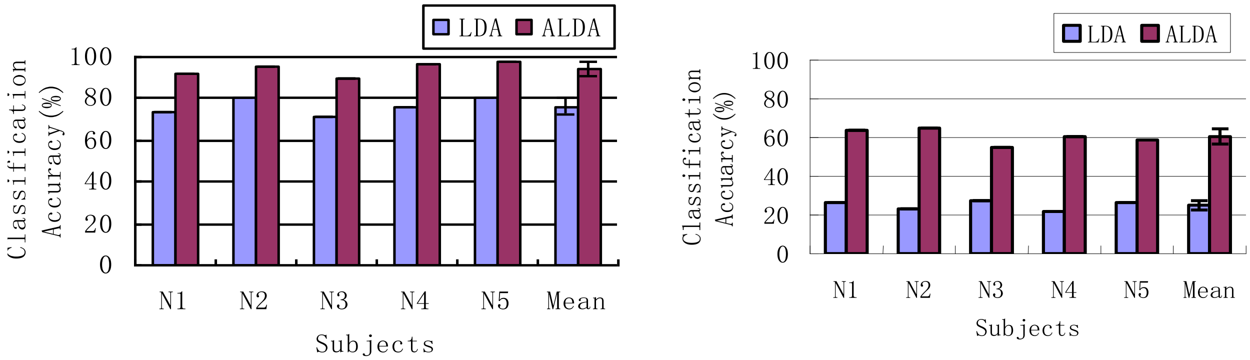

Fig.4. The classification accuracy of LDA and ALDA classifiers for each subjects at noise levels of 50% (left) and 200% (right), respectively.

IV. Discussion and Conclusion

A fluctuation of sEMG signal over time is inevasible due to its time-varying characteristic that may be caused by the changes of several factors, such as muscle fatigue, electrode shift, random interference, and sweating. Traditionally, supervised techniques such as LDA method have been proposed for motion classification in control of multifunctional myoelectric prostheses. With a trained LDA classifier, the changes of EMG recordings over time would decay its classification performance. In this case, an adaptive classifier would be needed to maintain the classification performance of a classifier. The study showed that the ALDA method would provide a good performance in noisy environment, and would promote the development of more robust control system for multifunctional myoelectric prostheses.

The ALDA classifier outperformed the commonly used LDA classifier due to its adaptive decoding algorithms. In the updating step, the parameters of ALDA were always computed from the latest training set, which could keep the adaptation property of the classifier and avoid the superimposing of error decision. Although this operation increased the computational time, it was acceptable because the calculation steps of updating parameters was not very complicated.

The proposed cycle substitution strategy was a compromise between the adaptation and steady capability of the ALDA method. The adaptive data were obtained in unsupervised conditions, just relying on the results of the linear discriminant. Note that continuous classification error might cause much misclassification and the classifier would therefore make incorrect decisions. As the original training data were supervised, the class labels were known clearly, and therefore the risk mentioned above was limited by part of the original training data. According to this study, 50% of the original training data might be a suitable cycle substitution proportion. Considering the size of all the training datasets was the same in this study, the effect of training-dataset size on the selection of cycle substitution will be studied for further research in the future.

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