ROBUST UPPER LIMB MOTION CLASSIFICATION USING GAUSSIAN MIXTURE MODELS

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Abstract– **A Gaussian mixture model (GMM) based classification scheme is proposed in this paper to perform multiple limb motion discrimination using continuous myoelectric signals (MES) from limb muscles. The system is optimized with respect to the feature set, classifier and post-end processing of the decisions through comprehensive experimentation. The experiments examine the effects of various feature sets including the time-domain (TD) features and the autoregressive (AR) features with root mean square value (RMS), and the effect of the majority vote (MV) in post-processing on the classification performance. The averaged GMM classification performance is compared with that of three other motion techniques (a linear discriminant analysis (LDA), a linear perceptron (LP) neural network and a multilayer perceptron (MLP) neural network). The Gaussian mixture motion model achieves 96.91% classification accuracy using a combination of AR with RMS and TD (AR+RMS+TD) feature set for a six class problem. It has been demonstrated that this GMM-based limb motion classification scheme has superior classification accuracy and results in a robust method of motion classification.**

I. INTRODUCTION

Electrically powered prostheses with myoelectric control have been found to have many advantages over other types of prostheses [2], mostly due to the autonomous nature of control. Pattern recognition of the MES is currently widespread used for prosthetic control system design.

In an attempt to increase the number of devices under the control of the MES, it is necessary to investigate a more sophisticated means to discriminate different muscle states [2]. In 1990, Hudgins presented a MES control scheme based upon simple time-domain (TD) features using a multilayer perceptron (MLP) artificial neural network with around 10% error for four types of limb motions [5]. In 1999, Englehart used a wavelet packet transform (WPT) with linear discriminant analysis (LDA) and an error rate of 6.25% was achieved for a four class problem [6]. In 2001, continuous MES classification scheme was developed that outperformed the transient MES system. The exceptional accuracy of 0.5% error for four classes and 2% error for six classes was achieved by using WPT, principal component analysis and LDA [8]. In [3], a real-time continuous control scheme was developed to discriminate four classes of limb motions using a TD feature set and a MLP classifier with an error rate of 6.75%. Chan first applied the Gaussian Mixture Models (GMM) on classification of MES with 6% error for a six-class problem [1]. Although the new classification techniques have shown improved performance, there remain many fascinating unsolved problems providing opportunities for progress.

GMMs have become the dominant approach in speaker recognition and verification over the past several years [4][7]. In this work, GMMs are applied to develop a continuous classification scheme for MES control. This work uses pattern recognition to process four channels of MES, with the task of discriminating six classes of limb motions. The approach demonstrates high classification accuracy, low computational complexity and system robustness.

II. METHODOLOGY

The design cycle of a GMM-based limb motion recognition system may be thought of as a multistage process including data collection, front-end processing, feature extraction, classification, post-end processing and performance evaluation as shown in Fig.1. This section describes the techniques involved in each stage.

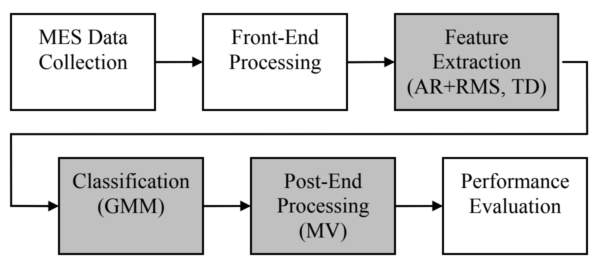


Fig. 1 The stages of the GMM-based motion classification system

A. Data Collection

The Data used in this work are the same as the data in [1][3]. Four channels of MES data were collected from 12 normal subjects. Four sessions were conducted for each subject. In each session, each subject performed six limb motions: wrist flexion, wrist extension, supination, pronation, hand open, and hand closed. Subjects performed each limb motion twice and each limb motion is held for five second durations in each session. Each subject underwent four 60s sessions. Subjects performed each motion in a definite order in the first and third sessions and in a random sequence in the second and fourth sessions. In this work, the first, second and third sessions were used as the training sessions and the fourth session was used as the test session.

B. Front-end processing

Limb motion classification is performed on 256 ms analysis windows. In an attempt to avoid transitory misclassification between classes, the 256ms sample window that overlapped a class transition point and the two 256ms adjacent windows to the overlapping record were eliminated from both the training and test sets.

The training data were segmented into disjoint 256ms windows such that each window contains new MES data. If the test data were processed in the same way, the system would produce a classification decision once every 256ms. However, it has been demonstrated that an alternative windowing scheme could efficiently produce a decision stream as dense as possible with the optimal window increment of 32ms called the overlapping windowing scheme [2]. The test data were segmented using the overlapping windowing scheme.

C. Feature Extraction

Four channels of MES were collected and subjected to feature extraction. Features were extracted from each of the four channels, and concatenated into a single feature vector which is then provided to the pattern classifier. In this work, the TD feature set [5] and the 6th-order AR+RMS feature set were examined.

The TD feature set consists of the number of zero crossings, the waveform length, the number of slope sign changes, and the mean absolute value. For each analysis window, a feature set is computed on each of four channels and then concatenated to form a 16 dimensional feature vector.

For each analysis window, a feature set which combined the 6th-order AR coefficients and the RMS (AR+RMS) was extracted on each channel. The feature set for each channel is a 7-dimensional feature vector. After concatenating the feature sets of four channels, the final feature set is 28-dimensional feature vector.

D. Classification

A Gaussian mixture density is a weighted sum of *M* component densities. A GMM is notated as $\lambda = \{w_i, \vec{\mu}_i, C_i\}$, *i=1,…,M*, by parameters of the mixture weights, mean vectors and covariance matrices. These parameters are estimated using the expectation-maximization (EM) algorithm respectively.

The GMM has some powerful attributes. The GMM not only provides a smooth overall distribution fit, its components also clearly detail the multi-modal nature of the density [6]. In addition, it is computationally inexpensive and is based on a well-known statistical model. Thus the GMM technique was applied to distinguish multiple limb motions.

In an effort to identify six classes of limb activities, six GMMs (λ_1, λ_2 ,…, λ_6) were applied to represent six motions. In the training session, the parameters of these six GMMs were estimated using EM algorithm. In the test session, each test pattern was subjected to these six GMMs and then six *posteriori* probabilities were computed. Finally, the maximum probability was selected and associated limb motion was labeled.

E. Post-end processing

It has been observed that a majority vote (MV) helps to filter out isolated misclassifications [1][2][3]. Therefore a MV technique was used at the post-end to process the decision stream to improve the accuracy of classification. For a given decision point D_i, the majority vote decision D_{MV} includes the previous *m* samples and the next *m* samples. The value of D_{MV} is simply the class with the greatest number of occurrences in this *(2m+1)* point window of the decision stream [2].

F. Performance Evaluation

The GMM classification performance of each subject was computed as the percent of incorrectly classified patterns over all test motions. The performance evaluation was averaged across 12 subjects; the results from each subject were averaged over ten trials to avoid the variance due to GMM initialization.

The performance of the GMM classification scheme was compared to the previous motion identification methods, including the LDA, LP and MLP.

III. EXPERIMENTS

This section provides a complete investigation of the multiple steps involved in the GMM-based limb motion classification scheme as shown in Fig.1. GMMs with diagonal covariance matrices and the variance limiting of 0.05 were applied in the following experiment. The MV technique was used unless indicated otherwise.

A. The Effect of the Feature Set Selection

In this experiment, the TD feature set, the AR +RMS feature set and the combination of AR+RMS and TD (AR +RMS+TD) feature set were subjected to the GMM-based limb motion classification system respectively. The purpose of this experiment is to compare the GMM classification performance using various feature sets to achieve an optimal feature configuration for the system. The criteria for determining an optimal feature set is a tradeoff of computational load versus classification performance.

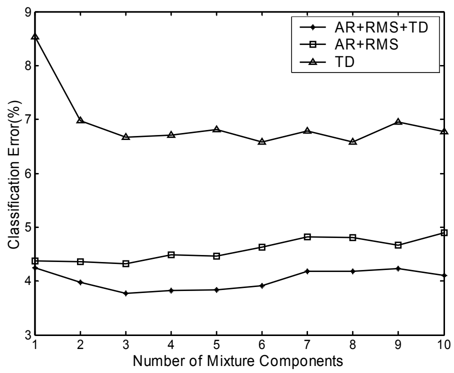


Fig.2 Averaged GMM classification performance for selected feature sets

The averaged classification performance across 12 subjects for three types of feature sets is illustrated in Fig.2. From this figure, the AR+RMS+TD feature set has the best performance over all different mixture numbers of the GMM, compared with either the AR +RMS feature set or the TD feature set. The AR+RMS feature set has much better accuracy than the TD feature set with more than 2% improvement which is a 35% improvement rate. The AR +RMS+TD feature set improves the classification accuracy slightly with approximate 0.5% improvement which is 15% improvement rate compared to the AR+RMS features.

The results demonstrate that the feature set selection is essential to the classification performance. Because the AR+RMS+TD feature set measures the combination of the AR+RMS features and the TD features of the MES for multiple limb motions, it produces the highest classification accuracy. However, due to the computational complexity of the AR +RMS+TD feature set, it should be used only if sufficient computational capacity is available.

B. Comparison to other limb motion classifiers

The TD feature set, the AR+RMS feature set and the AR+RMS+TD feature set were explored upon different motion classifiers including the GMM, LDA, LP and MLP in this experiment. The averaged classification performance for these feature sets are compared in Table 1. The aim is to compare the performance of the GMM with the other three classification methods using the same data and feature sets.

From Table 1, the GMMs with the optimal number of mixture components chosen for each subject (selected M) using the AR+RMS+TD feature set yields the best classification performance. The error rate of the GMMs with selected mixture components decreases to 3.09% which is 0.28% less error than the LDA and is 0.48% less error than the MLP. The GMM using the AR+RMS feature set also outperforms other motion techniques. The error rate for the GMM with selected components is 3.72% which is 0.7% less error than the LDA and 0.89% less error than the MLP. The GMM performance using TD feature set approaches the other motion models.

Table 1 Averaged classification performance for selected classifiers and feature sets

Model	Classification Error (%) AR+RMS+TD	Classification Error (%) AR+RMS	Classification Error (%) TD
GMM (Selected M)	**3.09**	**3.72**	5.80
GMM	3.77 (M=3)	4.32 (M=3)	6.57 (M=8)
LDA	3.37	4.42	**5.71**
LP	3.58	4.53	7.38
MLP	3.57	4.61	**5.71**

From the comparison, the GMM classifier outperforms other classifiers when the AR+RMS feature set was applied. It is observed that the GMMs with selected mixture orders for each subject have much better averaged classification performance than the GMMs with the optimal mixture order for all subjects.

C. The effect of a Majority Vote (MV)

To evaluate the efficacy of a MV upon the classification performance using the AR+RMS features, experimental results were obtained as follows.

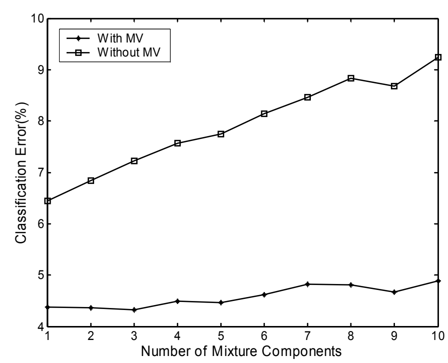
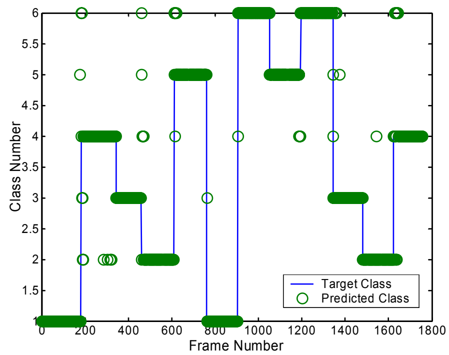
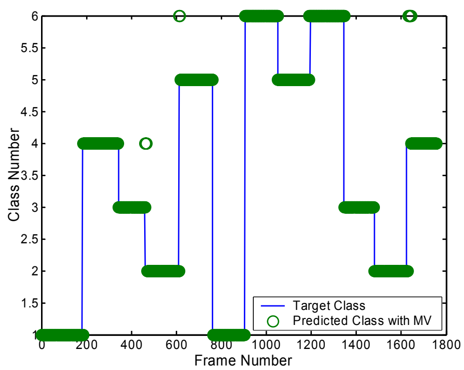


Fig. 3 The effect of a MV on the averaged GMM classification performance using the AR+RMS feature set.

Fig.3 shows the effect of a MV on the averaged GMM classification performance. We can see that a MV reduces the averaged classification error across various mixture numbers, especially for the high mixture numbers of the GMM. For the small mixture component GMMs, a MV improves the classification performance by roughly 2% while it dramatically improves the performance by roughly 4.3% for the large mixture component GMMs. Thus a MV "blunts" the effect of the number of mixture components upon the performance in the GMM-based limb motion classification system.



(a)



(b)

Fig. 4 The GMM predicted results of the test set with M=10 mixtures for subject #12. Figure (a) depicts results without MV; Figure (b) shows the results with MV.

Fig. 4 depicts the predicted results of the test set using the GMM, before MV and after MV. It can be noted that the prediction errors for the test set occur mostly at points of motion transition; it is clear that a MV has a dramatic effect on accuracy.

Table 2 The effect of a MV upon the averaged classification performance for selected classifiers using the AR +RMS feature set.

Model	Classification Error (%) Without MV	Classification Error (%) With MV	Improvement (%)	Improvement Rate (%)
GMM (Selected M)	6.06	**3.72**	2.34	39
GMM	6.44 (M=1)	4.32 (M=3)	2.12	33
LDA	5.74	4.42	1.32	23
LP	6.66	4.53	2.13	32
MLP	6.98	4.61	2.37	34

Table 2 shows the effect of a MV on the performance for selected models. It is observed that the effect of a MV on the classification accuracy is significant. A MV technique not only increases the GMM classification performance by around 35% improvement rate, but also yields very good results for the other motion classifiers.

IV. CONCLUSIONS

A GMM classifier has been developed for myoelectric control of powered upper limb prostheses. It has been demonstrated that the AR 6th-order + RMS feature sets have better performance than TD feature sets for the GMM-based limb motion classification scheme. The GMM allows six classes of motion to be classified with an average of 3.09% error rate which is superior to the LDA, LP and MLP classifiers. The MV technique improves the accuracy significantly by eliminating spurious errors. The work indicates that the GMM provides robust motion discrimination for the task of motion classification. Due to its low computational cost associated with its training, it will enable the possibility of online classifier training and allow the classifier to dynamically adapt to continuous changes.

The high accuracy of this method suggests that more challenging control problems can be addressed, such as simultaneous control of two motions. This work is currently under investigation and, if successful, would represent a dramatic improvement in the dexterity with which powered upper limb prostheses may be controlled.

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