MYOELECTRIC CONTROL DEVELOPMENT TOOLBOX

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INTRODUCTION

Surface myoelectric signals (MES) can be used as effective input for the control of upper arm prostheses. The concept of myoelectric control was introduced in the 1940's [1]. Initially, amplitude measures were used to parameterize the MES, but simple approach imposed a practical limit of a three state system for each MES control site (e.g. rest, hand open, and hand close) [2]; therefore, to implement a multifunctional prosthetic control system, additional MES control sites were required. Graupe and Cline [3] parameterized the MES using an autoregressive-moving-average model, instead of simple amplitude measures, and were successful at discerning multiple intended limb movements from a single MES control site. This result demonstrated that given the proper signal features, it was feasible to implement a multifunctional prosthetic control system.

Hudgins *et al.* [4] employed pattern recognition techniques to exploit the presence of a deterministic pattern during the onset of contractions. A system was constructed that was capable of discerning four limb motions, at an accuracy of around 90% for normally limbed subjects and around 85% for amputee subjects; however, users were required to control the system through contractions that were initiated from rest, preventing users from switching between states in a continuous and intuitive manner. In recent years, continuous myoelectric control methods have been developed to provide an intuitive user interface [5].

The process of pattern recognition can be broken down into three main phases: feature extraction, feature reduction, and classification. Within the system there may also be some pre-processing (e.g. amplification, filtering) and post-processing (e.g. smoothing). *Feature extraction* refers to the transformation of the input signal into a set of representative signal features. Zardoshti *et al*. [6], evaluated a number of features that are now commonly used for MES classification, including: integrated absolute value, zero crossings, and autoregressive coefficients. Other features including time-frequency features (e.g. wavelets and wavelet packets) have also been investigated [7].

The process of feature extraction may (and often does) result in feature vectors with high dimensionality. *Feature reduction* is employed to reduce the dimensionality, simplifying the task of the classifier and diminishing effect of the *curse of dimensionality* (i.e. the exponential increase in the feature space with the addition of each new feature) [8]. Ideally, feature reduction proceeds in a manner that reduces intra-class variations, while inter-class variations are maintained or enhanced. In addition to improving the *signal quality* and reducing the *noise*, feature reduction may also seek to reduce redundancies in the feature vector. Englehart *et al.* [7] compared principal component analysis (PCA) and feature selection based upon a Euclidean distance class separability. Chu *et al.* [9], employed a linear-nonlinear method combining PCA and a self-organizing feature map.

Classification maps feature vectors into specific classes, with the mapping function determined using training examples. Various classification methods have also been employed including linear discriminant classifiers [7], multi-layer perceptrons (MLP) [7][9], fuzzy systems [10], hidden Markov models [11], and Gaussian mixture models [12].

While research in pattern recognition for myoelectric control is quite abundant, the ability to adequately compare methods is wanting. Indeed, results are quite dependent upon the data and implementation details. In this paper, we describe a simplistic pattern recognition system which is based on a linear discriminant classifier. This system is used to compare feature reduction methods, which demonstrates superior performance of uncorrelated LDA (ULDA) to PCA feature reduction. The source code for this implementation is made publicly available with the intent that this method will form a common baseline measurement against which other algorithms can be compared. There will be a continual expansion of the publicly available tools to include newer methods as research in this topic area progresses.

METHODS

Development of this pattern recognition library is performed using Matlab (Mathworks Inc., Natick, MA).

Note that some of the code has dependencies on functions from certain Matlab toolboxes. Other dependencies on other third party toolboxes will be explicitly noted. This pattern recognition library is available at http://www.sce.carleton.ca/faculty/chan.

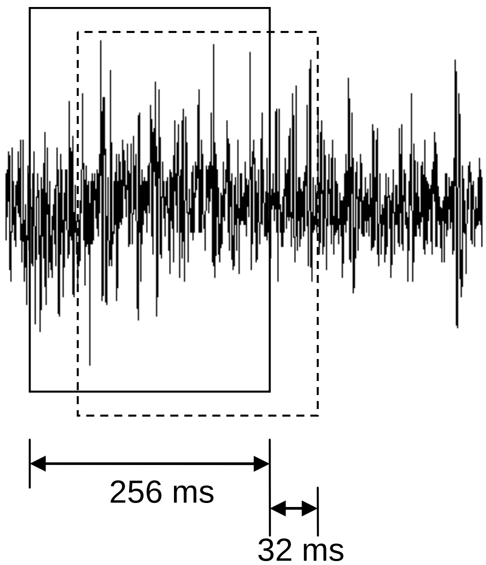

Figure 1: Sliding analysis window

Feature Extraction

Features are computed from the MES using a sliding analysis window. An example of the sliding window is depicted in Figure 1, shown with analysis windows of 256 ms in length, spaced 32 ms apart. A single feature vector is produced from each analysis window.

Feature extraction methods that have been implemented include features for: root mean square, mean absolute value, integrated absolute value, autoregressive coefficients, zero crossings, and slope sign changes.

Feature Reduction

Feature reduction methods that have been implemented are PCA and ULDA. PCA is an unsupervised method (i.e. the method does not require class labels) of feature reduction. It is a statistical method that identifies the linear projection of features that correspond to the principal variations in the data. LDA is a supervised method (i.e. the method uses features with class labels), which maximizes the ratio of the between-class distance to the within-class distance. This method suffers from the problem of singularity in the scatter matrix that occurs in undersampled problems (i.e. when the feature vector dimension is much larger than the sample size). ULDA is an enhancement to LDA, which imposes the additional requirement that reduced features be statistically uncorrelated with one another; thus, minimizing redundancies. The singularity problem is resolved using the generalized singular value decomposition [13].

Classification

Classification is simply performed using an linear discriminant classifier. The advantage of this classifier is that it does not require iterative training, avoiding the potential for under- or over-training. In addition, a high dimensionality problem can be well linearized during feature reduction if done properly. This reduces the potential that non-linear classifiers, such as MLPs, will achieve high classification accuracies.

Data

Example data were used to demonstrate this pattern classification toolbox. These data are the same data used in [14], which were collected from 30 subjects. MES were collected from seven sites on the forearm and one site on the bicep using Duo-trode Ag-AgCl electrodes (Myotronics, 6140). An Ag-AgCl Red-Dot electrode (3M, 2237) was placed on the wrist to provide a common ground reference. These signals were amplified (Model 15, Grass Telefactor), with a gain of 1000 and bandwidth of 1 Hz to 1 kHz. Signals were sampled at 3 kHz using an analog-to-digital converter board (National Instruments, PCI-6071E). MES data were downsampled to 1 kHz prior to pattern classification.

MES data were collected as the subject underwent seven distinct limb motions: hand open, hand close, supination, pronation, wrist flexion, wrist extension, and rest. Within each trial, the subject repeated each limb motion four times, holding each motion for a duration of three seconds each time. The order of these limb motions was randomized. A five-second rest period was introduced at the start and end of each trial to avoid data being cutoff while collecting the data, making each trial 94 seconds in length. A total of six trials were complete in a session, with four sessions completed on four separate days.

In this paper, data from only session four were used. Data from the first two trials were used as training data and data from the remaining four trials were used as testing data. The first four autoregressive coefficients and the root mean square value were used as the feature vector (dimensionality is 40 = 8 channels $\times$ 5 features/channel). The analysis window size was 256 ms (it is generally agreed that a delay that is less then 300 ms is acceptable for myoelectric control [5]), which were spaced 128 ms apart for training data and 32 ms apart for testing data. Data that were 256 ms before or after a change in limb motion were removed from the training set to avoid transitional data.

RESULTS

The classification error from the testing data was 10.56% (with no feature reduction). To improve classification accuracy, majority vote post-processing can be employed. The majority vote uses the current classification result, along with the previous 8 classification results (with an analysis window spacing of 32 ms, this corresponds to the classification results within the last 256 ms) and makes a classification decision based on the class that appears most often (Figure 2). The resulting effect is a smooth operation that removes spurious misclassification. Indeed, the classification error reduces to 9.39% after majority vote post-processing.

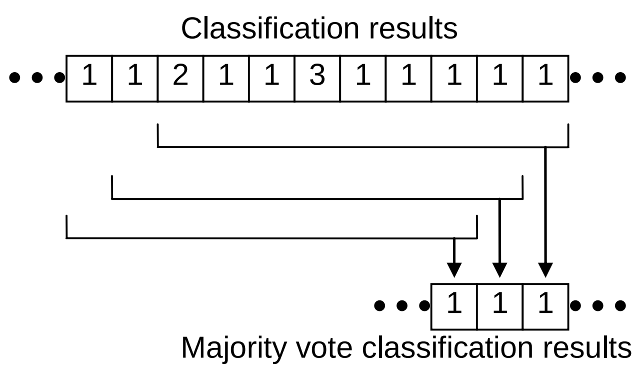

Figure 2: Majority vote post-processing

A plot of the classification sequence is shown in Figure 3. One can see that the pattern recognition algorithm is quite successful at classifying the MES data. The errors that are present occur during transitional periods, which are expected as the system is in an undetermined state between contractions. Indeed, if we removed the analysis windows that are 256 ms before and after the transition, the classification error is 7.46%.

The reason why feature reduction was not needed with these data is twofold. First, we have a *rich* training data set, which is important in any classification problem. Simply stated the number of training data and the diversity of the training data should be representative of the data that one would encounter in the test data. The second factor is the high dimensionality of the feature vector, which increase the probability that the data can be linearly separable.

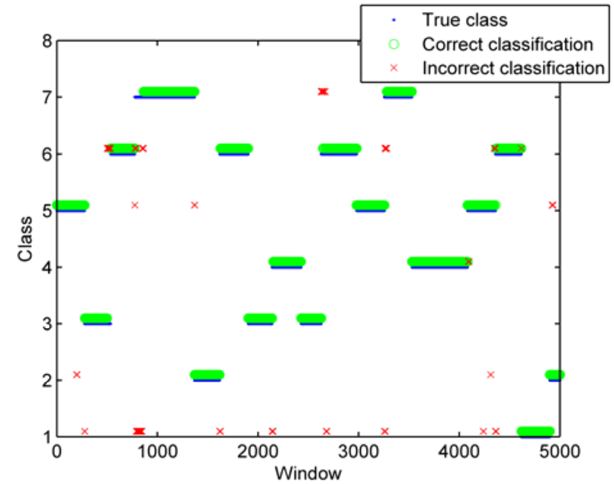

Figure 3: Classification sequence

Figure 4 is a plot of the classification accuracy as a function of the feature dimensionality. Feature reduction was performed by randomly selecting features (the plot includes the mean and standard deviation of a 10 trials), PCA, and ULDA. As expected, increasing the dimensionality of the feature vector reduces the classification error. For the random selection of features, the classification error does not reach its minimum until all the features are selected.

PCA reduces the feature dimensionality by selecting a new feature space based on the eigenvectors with the largest eigenvalues. Essentially, this keeps the parts of the data with the highest variance. These parts often contain the “most important” information for discrimination; however, this is not necessarily true. Examining Figure 4, we can see that the addition of each new principal component does result in a large decrease in classification error, especially compared to a method that randomly selects features; however, it is does not reach its minimum until all the features are selected.

Figure 4 clearly shows that ULDA outperforms PCA. This is not unexpected because PCA is an unsupervised feature reduction method, while ULDA is a supervised method. Instead of simply choosing feature projections based on variance, ULDA chooses feature projections that optimize class separability. The resultant feature vector, after feature reduction, will have a dimensionality that is less than the number of classes. In this analysis, the number of classes is seven, and ULDA attains the minimum classification rate with six features. Indeed, this is why Figure 4 only plots ULDA results for six features or less.

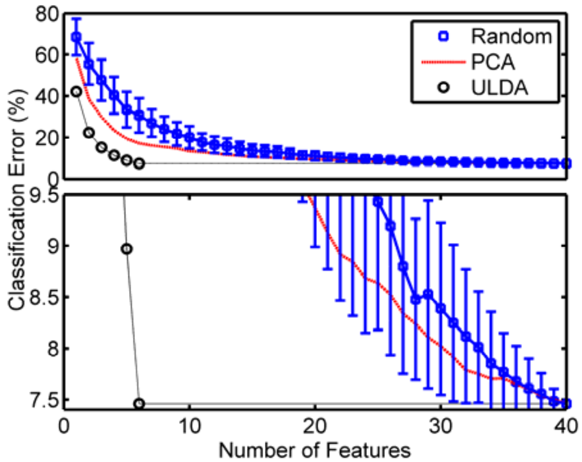

Figure 4: Classification accuracy as a function of the feature vector dimensionality

DISCUSSION

Results in this paper demonstrate that a relatively simple pattern classification system can achieve high classification accuracy. One can improve classification accuracy by changing the pattern recognition components in the system. For example, different features, feature reduction methods, and classifiers may yield an improved system. The system presented in this paper establishes a good baseline to which other systems can be compared. This includes comparisons in system complexity. This is of particular importance for myoelectric control systems, where the computational requirements are important in an embedded system implementation (e.g. computation load, power requirements, system robustness).

This paper also compares two different feature reduction methods: PCA and ULDA. While PCA is shown to be more effective than random selection, the minimum classification error is not achieved when PCA feature reduction is used.

Results clearly demonstrate that ULDA outperforms PCA feature reduction. The feature vector can be reduced by almost a factor of 7, without any increase in classification error. This significantly simplifies the task of the classifier. Indeed, classifiers using machine learning algorithms (e.g. MLPs) could be trained faster and be less susceptible to over- or under-training.

CONCLUSIONS

A simplistic pattern recognition system for myoelectrically controlled upper arm prostheses is presented. This system uses RMS and autoregressive coefficients as features. Effective feature reduction is demonstrated using ULDA. With a linear discriminant classifier, an average classification accuracy of 92.54% was achieved over 30 subjects.

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