PRINCIPAL COMPONENTS ANALYSIS TUNING FOR IMPROVED MYOELECTRIC CONTROL

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ABSTRACT

Information extracted from signals recorded from multi-channel surface myoelectric signal (MES) recording sites can be used as inputs to control systems for powered prostheses. For small, closely spaced muscles, such as the muscles in the forearm, the detected MES often contains contributions from more than one muscle; the contribution from each specific muscle being modified by a tissue filter between the muscle and the detection points. In some cases the contributions from very small/deep muscles are masked by those from larger/superficial muscles. In such circumstances, subtle changes in muscle activations associated with different movements may not be easily detectable. In this work, the measured raw MES signals are rotated by class specific rotation matrices to spatially decorrelate the measured data prior to feature extraction. This tunes the pattern recognition classifier to better discriminate the test motions. Preliminary work indicates that this additional preprocessing step significantly reduces classification errors.

INTRODUCTION

The myoelectric signal (MES) has been effectively used as a control input to powered prosthesis for over 40 years [1]. The ultimate goal in limb replacement, from a control perspective, is to provide the user with a device that is intuitive to control and is capable of independent, simultaneous activation of multiple degrees of freedom. This is a very challenging problem. The simplest form of control can be realized by mapping an estimate of the amplitude [2], or rate of change of the amplitude [3] of a given MES site to one degree of actuation of the prosthetic device. These systems work well and are intuitive to use provided a portion of a physiologically appropriate muscle remains on the residual limb from which the MES can be measured. Generally, this type of control system is capable of controlling only one or two degrees of freedom due to a limited number of independent control sites remaining on the residual limb. Information extracted from patterns contained in the myoelectric signal can also be used for control purposes. A robust state-of-the-art continuous pattern recognition based myoelectric control system capable of providing real-time sequential multifunction control was described in [4]. Briefly, this control system consists of signal detection, feature extraction, dimensionality reduction, classification, and post-processing in the form of majority voting. A variety of feature extraction, dimensionality reduction, and classification techniques have been investigated and reported in the literature.

The surface MES is an electrophysiological signal generated by a muscular contraction which propagates along the length of skeletal muscle to detection points on the skin's surface. For small, closely spaced muscles like those in the forearm, the detected MES often contains contributions from more than one muscle; the contribution from each specific muscle being modified by a tissue filter between the muscle and the detection points. In some cases the contributions from very small/deep muscles are masked by those from larger/superficial muscles and it is possible for these subtle changes in muscle activation, associated with varying movements, to go undetected. Because pattern recognition based myoelectric control systems rely on repeatable, distinct patterns being identified in the MES at the electrode locations, it is desirable to distinguish even the most subtle changes. This work introduces an additional pre-processing step to a pattern recognition based myoelectric controller which acts as a "tuner" for each specific class in order to extract the most pertinent information and reduce classification errors.

METHODOLOGY

Experimental Protocol

MES data corresponding to twelve classes of motion were collected from 4 healthy subjects using an assistive brace developed by Hargrove et al [5] for performing static contractions. All experiments were approved by the University of New Brunswick's Research Ethics Board. Five or six electrodes were placed around the forearm, depending on size; chosen to optimally encompass the circumference of the arm.

Subjects were prompted to perform eight repetitions of the following 11 types of contraction: wrist pronation/supination, wrist flexion/ extension, wrist abduction/adduction, hand open, key grip, chuck grip, power grip, pinch grip and a no movement/rest class. Each contraction was held for 4 seconds. The first four repetitions were used as training data, and the final four for testing. Data were collected using a custom built pre-amplification system, a 16-bit DAQ and custom data acquisition software, sampling at 1kHz.

Data Processing

The pattern recognition control system described in [4] with the additional data pre-processing block is shown in Figure 1a. The focus of this paper is on the improvement gained by the addition of the pre-processing block and the reader is referred to [4] for a thorough description of the remainder of the system.

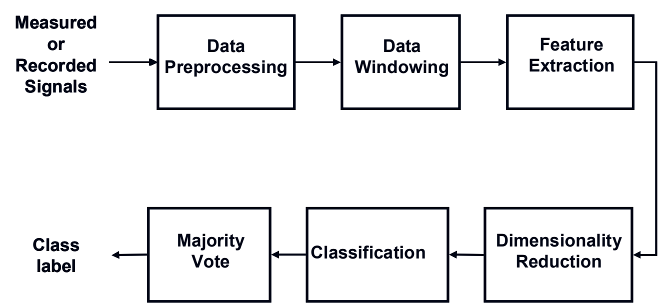

Figure 1: The basic steps of pattern recognition based myoelectric control.

Previous work for similar data sets has shown that (TD), auto-regressive coefficient (AR), or concatenated TD and AR (TDAR) features all yield good classification performances as inputs to a linear discriminant analysis (LDA) classifier for the motions under investigation [5]. Consequently, these feature sets and classifier will be used to assess the relative performance effect of the pre-processing block. Features were extracted from 250ms data windows and no dimensionality reduction or majority voting was used.

Principal Components Analysis (PCA) is a linear transformation which linearly decorrelates multivariate data and projects it onto a new coordinate system such that the greatest variance in the data lies on the first coordinate while the least variance in the data comes to lie on the last coordinate [6]. The PCA transformation matrix will be different for each motion class if; 1) different degrees of muscle crosstalk are present at the electrodes for different motions, or 2) the signals detected at the electrodes are uncorrelated but are of different relative amplitudes. The first point is a result of the decorrelation property of PCA while the second point stems from the ordering of the principal components (PCs) from maximum to minimum variance. The PCA tuning algorithm projects data down class specific PCA transformation matrices (which are found using the training data for each specific class) and then extracts features from the rotated data as shown in Figure 2.

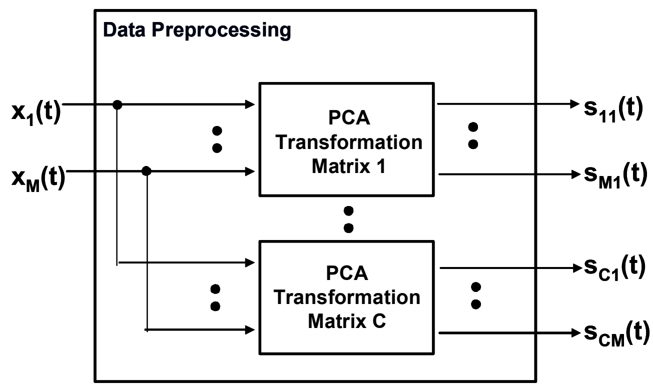

Figure 2: A block diagram showing the PCA tuning preprocessing block. This form of signal processing increases the dimensionality of the input by a factor of C where C is the total number of motion classes.

It is hypothesized that the projection down the appropriate PC transformation matrix will enhance or 'tune' the data while projection down the remaining PC transformation matrices will result in less meaningful linear combinations of the measured multivariate data. A similar algorithm has been successfully implemented to improve recognition of facial patterns in the context of image processing [7].

It can be seen in Figure 2 that the PC tuning algorithm increases the dimensionality of the inputs by a factor of C where C is the total number of classes. This could be problematic due to the 'curse of dimensionality' [8]; high dimensional space requires much more training data than low dimensional space to ensure that dense decision boundaries are formed. Consequently, either much more training data must be collected or feature reduction techniques need to be employed. It is desirable to use feature reduction techniques for two reasons; 1) shorter training sessions are more convenient for a prosthetic user and 2) less features improve the real-time performance of the classifier.

A simple channel growing algorithm was used to reduce the dimensionality of the data. This algorithm iteratively adds the most informative linearly combined channels, as determined by empirical classification performance. In the first iteration of this method, each channel was used, independently, to train and subsequently test classification performance. The channel producing the highest classification accuracy was chosen as the first channel of the reduced subset. For the next iteration, the first optimal channel was paired with each of the remaining channels to form a 2-channel EMG data set for classification. The pair of EMG channels generating the highest classification accuracy was considered the best two-channel subset. This procedure was repeated until the classification performance reached a plateau or began to decrease as a result of the increased dimensionality of the data.

RESULTS

Figure 3 provides a comparison of the classification performance resulting from using the PCA tuning algorithm. It is clear from Figure 3 that the PCA tuning algorithm, with no data reduction, reduces the classification errors for each of the feature sets under investigation; on average there is a 49%, 40% and 34% improvement for the TD, AR and TDAR feature sets while the PCA tuning with data reduction reduces the error by 71%, 73% and 75%.

Figure 4 displays a confusion matrix averaged over the four subjects for the TD feature set. The confusion matrix allows for a comparison of the classification performance, decision results on a class by class basis. It is observed that PCA tuning results in improvements or no change in all classes except hand open, which displays a slight decrease in classification accuracy.

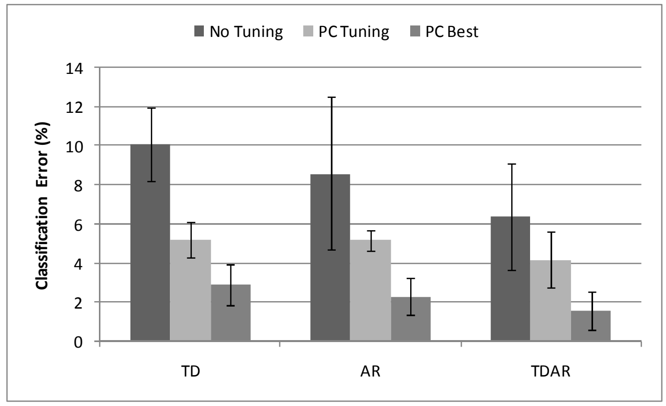

Figure 3: A comparison of classification errors resulting from processing with and without PCA tuning. The PC Best is a result of using PCA tuning with the iterative channel growing algorithm. Error bars show 1 standard deviation of the intersubject variability.

DISCUSSION

The PCA tuning algorithm yields more accurate myoelectric control schemes; however, it does increase the complexity of the classifier. It is important that a decision be made by the pattern recognition based myoelectric control scheme within 300ms of initial intent, which is the upper limit of an acceptable delay to the user. Given a 250ms analysis window, approximately 50ms remains in which a decision must be made. Current embedded systems under development for controlling powered prostheses can easily implement the PCA tuning algorithm within this time constraint. Alternatively, one could shorten the analysis window to 125 ms to make faster decisions at the expense of a slight degradation of classification performance [4].

	Pronation		Supination		Flex		Extend		Abduction		Adduction		Hand Open		Key		Chuck		Power		Pinch		Rest	
Pronation	92.4	97.1	0.0	0.0	0.0	0.0	0.0	0.0	1.8	0.1	0.1	0.0	0.0	1.4	0.0	0.0	1.3	0.2	0.0	1.0	4.1	0.1	0.4	0.2
Supination	0.0	0.0	99.3	99.8	0.0	0.0	0.3	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.2	0.2	0.0	0.0	0.0	0.0	0.0
Flex	0.5	0.3	0.0	0.0	99.3	99.7	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Extend	0.1	0.0	0.1	0.0	0.0	0.0	90.3	99.1	7.3	0.4	0.0	0.0	1.5	0.4	0.0	0.0	0.6	0.0	0.0	0.0	0.2	0.1	0.0	0.0
Abduction	0.1	0.2	0.1	0.0	0.0	0.0	6.0	0.3	76.0	89.1	0.0	0.0	6.0	6.3	0.0	0.0	11.7	4.0	0.0	0.0	0.2	0.2	0.0	0.0
Adduction	3.5	6.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	85.9	88.6	2.7	3.5	7.7	1.4	0.0	0.0	0.0	0.0	0.3	0.3	0.0	0.0
Open	0.0	0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.9	0.5	2.6	96.5	93.4	0.0	0.1	1.0	1.1	0.0	0.0	1.8	1.7	0.0	0.0
Key	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0	0.0	99.0	99.4	0.3	0.0	0.7	0.6	0.0	0.0	0.0	0.0
Chuck	0.0	0.0	0.0	0.0	0.0	0.0	7.2	0.5	0.7	0.2	0.0	0.0	0.0	0.0	0.0	0.0	76.1	91.9	0.0	0.0	14.8	7.3	1.3	0.2
Power	0.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0	4.7	0.5	0.0	0.0	0.1	0.0	12.8	9.4	2.1	2.2	78.9	87.5	1.2	0.4	0.0	0.0
Pinch	0.0	0.0	0.0	0.0	0.0	0.0	0.9	0.2	0.1	0.0	0.0	0.0	0.0	0.8	0.0	0.0	13.4	6.7	0.0	0.0	85.6	92.3	0.0	0.0
Rest	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.4	0.0	0.0	0.7	0.0	99.3	99.6

Figure 4: Confusion matrix for the TD feature set averaged over the four subjects. The values in white (left columns) show processing without PCA tuning the values in grey (right columns) show the results with PCA tuning with no data reduction. The results along the main diagonal are correct classifications (accuracy), and those lying outside of the main diagonal are incorrect classifications (error rate).

The relationship between classification accuracy and prosthesis controllability has yet to be clearly defined [9]. Although PCA Tuning yields a more accurate system, a usability test needs to be completed to determine if the increased classification accuracy provided by the algorithm translates to increased controllability of a prosthesis. Furthermore the application of the algorithm to shorter data windows should also be investigated to ensure that the improvements gained for 250 ms windows translate are applicable to shorter window lengths. Recent research has suggested that although shorter window lengths result in a slightly less accurate system, it would be more controllable by the user [10].

Although the iterative channel growing algorithm yields good results, a more robust method of data reduction is needed. As the algorithm is currently implemented, each channel was used, independently, to train and subsequently test classification performance. Consequently the channel growing algorithm is highly dependent on the test data. Different supervised and unsupervised data reduction techniques are currently being investigated.

CONCLUSIONS

A novel PCA tuning algorithm implementation was introduced for use with existing MES pattern recognition based prosthetic control systems. MES data were projected onto class specific PCA transformation matrices for tuning, prior to pattern recognition classification. This pre-processing was shown to increase class separability for classification by a LDA classifier. Classification error was reduced by 49%, 40% and 34% when using TD, AR and TDAR feature sets, respectively.

A brute force channel reduction algorithm was used to further reduce the dimensionality of the data, resulting in an error reduction of 71%, 73% and 75% for the same feature sets. Further improvements may be achieved by implementing a more focused dimensionality reduction algorithm. The effect of increased accuracy due to preprocessing on prosthesis usability remains a topic of research and investigation.

ACKNOWLEDGEMENTS

This work was supported by NSERC Discovery Grants 171368-03 and 217354-01, the Research Assistantship Initiative (RAI) of the New Brunswick Innovation Foundation (NBIF), and the Atlantic Innovation Fund (AIF).

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