Proceedings of the 29th Annual International
Conference of the IEEE EMBS
Cité Internationale, Lyon, France
August 23-26, 2007.

Principal Components Analysis Preprocessing to Reduce Controller Delays in Pattern Recognition Based Myoelectric Control

L. Hargrove, *Student Member, IEEE,* E. Scheme, *Member IEEE*, K. Englehart, *Senior Member, IEEE,* and B. Hudgins, Senior *Member, IEEE*

***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 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. Using this preprocessing step, MES analysis windows may be cut from 256 ms to 128 ms without affecting the classification accuracy.**

I. Introduction

The myoelectric signal (MES) has proven to be an effective control input to powered prostheses for over 40 years [1]. Conventional myoelectric control strategies are control strategies which have found widespread clinical use. They are often used in conjunction with body powered harnesses, mechanical switches, and force sensitive resistors as part of a conventional prosthesis control strategy. The three-state amplitude controller [2], three-state rate sensitive controller [3], direct control [4], and myo-pulse controller [5] are all examples of conventional myoelectric control strategies. 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 provided repeatable patterns can be generated by the patient at the control site locations. A robust state-of-the-art continuous pattern recognition based myoelectric control system capable of providing real-time sequential multifunction control was described in [6]. Briefly, this control system consists of signal detection, feature extraction, dimensionality reduction, classification, and post-processing in the form of majority voting.

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.

II. Methodology

A. 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 [7] 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 forearm 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, the next two were used as a validation set, and the final two were used for a test set. Data were collected using a custom built pre-amplification

L. Hargrove a Phd candidate at the Institute of Biomedical Engineering at the University of New Brunswick, Fredericton, NB Canada. (506-458-7032, e-mail: levi.hargrove@unb.ca)

E. Scheme is a Research Engineer with the Institute of Biomedical Engineering at the University of New Brunswick, Fredericton, NB, Canada, (email: escheme@unb.ca)

K. Englehart is Associate Director of the Institute of Biomedical Engineering at the University of New Brunswick, Fredericton, NB Canada. (e-mail: kengleha@unb.ca).

B. Hudgins is Director of the Institute of Biomedical Engineering at the University of New Brunswick, Fredericton, NB, Canada. (e-mail: hudgins@unb.ca).

This work was supported by NSERC Discovery Grants 171368-03 and 217354-05, the Research Assistantship Initiative (RAI) of the New Brunswick Innovation Foundation (NBIF), and the Atlantic Innovation Fund (AIF).

system, a 16-bit DAQ and custom data acquisition software, sampling at 1 kHz per channel.

B. Data Processing

The pattern recognition control system described in [6] with the additional *data pre-processing* block is shown in Figure 1. The focus of this paper is on the improvement gained by the addition of the pre-processing block and the reader is referred to [6] for a thorough description of the remainder of the system.

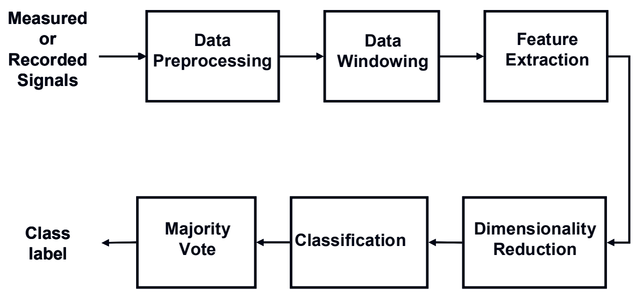

Figure 1: The basic steps of pattern recognition based myoelectric control.

Previous work for similar data sets has shown that time-domain (TD) features as inputs to a linear discriminant analysis (LDA) classifier results in high classification accuracy for the motions under investigation [7]. Furthermore, this system is also computationally efficient, facilitating embedded systems implementations which make class decisions with a processing delay of less than 10 ms. Consequently, this feature set and classifier will be used to assess the relative performance effect of the pre-processing block. Window lengths of 64, 128, and 256 ms will be investigated.

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 [8]. 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.

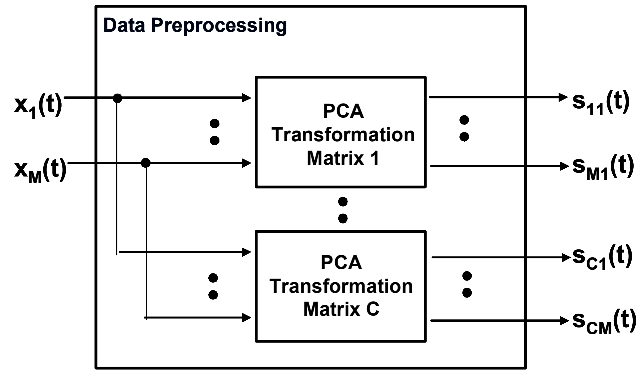

Figure 2: A block diagram showing the PCA tuning preprocessing block. This form of signal processing increases the dimensionality of the input by a factor of C where C is the total number of motion classes.

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 [9].

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. It is very likely that some of the output channels from the PCA tuning algorithm contain some redundant information and thus the number of linearly combined channels can be reduced. A simple iterative sequential backward selection (SBS) algorithm was used to reduce the dimensionality of the data [10]. This algorithm iteratively discards the least informative linearly combined channel, as determined by the empirical classification performance of the validation set. The SBS algorithm was used to reduce the number of channels to 25 as this provided good classification accuracy. The PCA tuning algorithm can easily be implemented in real-time using this number of channels.

III. Results

Figure 3 displays the results of the PCA turning algorithm using three different window lengths. It can be seen that using PCA tuning either with or without channel reduction results in classification error reduction of approximately 5-6% for the three different cases. Table 1 shows the confusion matrix averaged across subjects using 128 ms data analysis windows with the number of linearly combined channels reduced to 25 using the SBS algorithm. The confusion matrix indicates which motions are being erroneously classified. The row indicates the desired class and each column represents the percentage of time that motion was selected. Ideally, the table would contain 100 % in the diagonal elements and 0 % in the off diagonal elements.

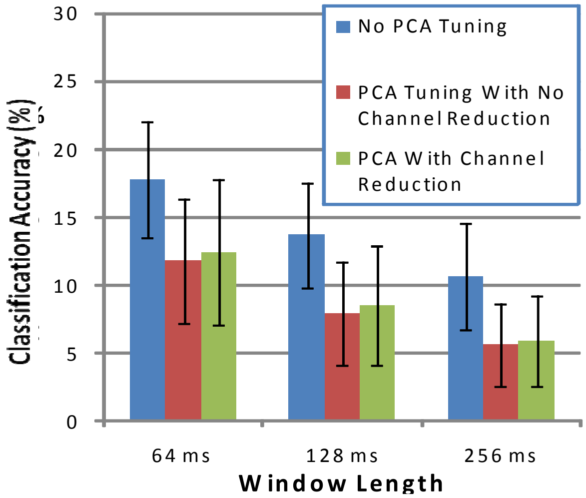

Figure 3: A comparison of classification errors resulting from processing with and without PCA tuning. Error bars show 1 standard deviation of the intersubject variability.

IV. Discussion

PCA tuning resulted in classification error improvements of approximately 5 % for all investigated window lengths. This represents relative improvements of 33%, 40%, and 47 % for the 64, 128, and 256 ms window length cases. It appears that the 5% improvement remains regardless of window length suggesting that the improvement gained by PCA tuning is independent of analysis window length. It should be noted that the relationship between classification accuracy and myoelectric usability has yet to be clearly defined [11] and more work is required to determine how improvements to *classification accuracy* due to PCA tuning translate to classifier usability. Indeed, usability appears to be influenced by classification accuracy, controller delay, and the mental burden required to affect control. Each of these factors, in turn, are interrelated.

Figure 3 clearly supports the assertion that longer analysis windows result in a more accurate control system; however there is a tradeoff between controller delay and prosthesis usability. Ranges of acceptable controller delays vary in values from 50 ms [12] up to 400 ms [13]. PCA tuning with 128 ms windows maintains lower classification error when compared with no PCA tuning and 256 ms analysis windows. Thus the PCA tuning should result in a more usable myoelectric control system due solely to the ability to use *shorter window lengths* which in turn reduces the overall controller delay.

The PCA tuning algorithm increases the computational load in the feed-forward mode of operation because of two factors: 1) the *M* x *CM* matrix multiplication (M channels by C classes) to rotate the raw data and 2) features must be extracted from the resulting *CM* number of channels. This algorithm would be unable to meet the real-time processing delay target of less than 10 ms. Consequently, it was necessary to reduce the number of channels to improve the processing speed and reduce the computational load. Using the SBS algorithm, 25 channels were retained from which to make a decision. When channel reduction is used, the PCA tuning algorithm requires a (M x 25) matrix multiplication resulting in 25 channels from which features need to be extracted to classify the 12 motion classes. Current embedded systems under investigation can meet this operating requirement. Figure 3 shows that reducing to 25 channels using the SBS algorithm does not significantly compromise classification error improvement gained through PCA tuning.

Table 1 shows the average error distributions across subjects for the 128 ms analysis window. It is noted that in the majority of cases, PCA tuning improves the class specific classifications accuracies or it remains the same. Furthermore, it is noted that most of the classification errors occur in the hand grips. This is not surprising as there are only subtle differences in these motions.

The PCA tuning algorithm can easily be extended using independent components analysis (ICA) as a pre-processor. The implementation of the algorithm would mirror that of PCA tuning; however an ICA separation matrix would be found for each motion from the training data and the test data would be projected down these matrices prior to classification.

TABLE 1
CONFUSION MATRICES FOR TD FEATURE SET WITH 205 MS ANALYSIS WINDOWS AVERAGED OVER THE 4 SUBJECTS

	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

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).

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 reduce classification errors on average by 5%, independent of analysis window size. This translates to relative classification error improvements of 33%, 40% and 47% when using window lengths of 64 ms, 128 ms, or 256 ms.

The SBS channel reduction algorithm was used to reduce the dimensionality of the data to 25 channels, resulting in a method that can be implemented in an embedded system within the requisite 10 ms processing time. Future work will investigate PCA tuning as a preprocessor to other classification algorithms and will also investigate PCA tuning as a preprocessor for data sets containing combined motions.

REFERENCES

[1] P. Parker, K. Englehart, and B. Hudgins, "Myoelectric signal processing for control of powered prosthesis", *Journal of Electromyography and Kinesiology*, vol 16, no. 6, pp. 541-548, Dec. 2006.

[2] D. S. Dorcas, and R.N. Scott, "A three-state myoelectric control," *Med. Biol. Eng*., vol. 4, pp. 367-372, 1966.

[3] D. A. Childress, "A myoelectric three state controller using rate sensitivity," *in Proc. 8th ICMBE*, Chicago, IL, pp. S4-S576, 1969.

[4] A. E. Kobrinski, et al., "Problems of bioelectric control," Automatic and Remote Control, *Proceedings of the 1st IFAC International Congress*, vol. 2, J. F. Coles, ed., vol. 2, London, England, pp. 619-623, 1960.

[5] D.S. Childress, "An Approach to Powered Grasp," *presented at Fourth International Symposium on External Control of Human Extremities*, Belgrade, Yugoslavia, 1973.

[6] K. Englehart and B. Hudgins, "A robust, real-time control scheme for multifunction myoelectric control," *IEEE Transactions on Biomedical Engineering*, vol. 50, no. 7, pp. 848-854, July 2003.

[7] L. Hargrove, "A comparison of Surface and Intramuscular Myoelectric Signal Classification", Master's Thesis, University of New Brunswick, 2005.

[8] A. Hyvarinen, E. Oja, and J. Karhunen, Independent Component Analysis. New York: John Wiley & Sons, 2001

[9] K. Vanketaramani, S. Qidwai, and B Vijayakumar, "Face authentication from cell phone camera images with illumination and temporal variations", *IEEE Trans. On Systems, Man, and Cybernetics*, vol. 35, No. 3, pp. 411-418, Aug 2005

[10] P. Somol, P. Pudil, J. Novovicova and P. Paclik, "Adaptive floating search methods in feature selection", *Pattern Recognition Letters* vol. 20, pp 1157-1163, 1999.

[11] B. Lock, K. Englehart, B. Hudgins, "Design and interactive assessment of continuous multifunction myoelectric control systems", *Proceedings of the Myoelectric Controls Symposium* '05, Fredericton, Canada, Aug. 2005.

[12] D. S. Childress and R. F. Weir, "Control of Limb Prostheses," in Atlas Of Amputations and Limb Deficiencies: Surgical, Prosthetic, and Rehabilitation Principles, 3rd Edition, D. G. Smith, J. W. Michael, and B. J.H., Eds., 3rd ed. Rosemont, IL: American Academy of Orthopaedic Surgeons, 2004, pp. 173-195.

[13] G. Hefftner, W. Zucchini, and G. G. Jaros, "The electromyogram (EMG) as a control signal for functional neuromuscular stimulation--Part I: Autoregressive modeling as a means of EMG signature discrimination," *IEEE Trans Biomed Eng*, vol. 35, pp. 230-7, 1988

[14] T. Farrell and R. F. Weir, "The Optimal Controller Delay for Myoelectric Prostheses", *IEEE Trans on Neuroscience and Rehabilitation Engineering*, vol 15, no. 1, pp. 111-118, March 2007.