Myoelectric Signal Segmentation And Classification Using Wavelets Based Neural Networks

Yousef Al-Assaf and Hasan Al-Nashash
{yassaf, hnashash}@aus.ac.ae
School of Engineering, American University of Sharjah, P.O.Box 2666, Sharjah, UAE

Abstract- **In this paper a method for Myoelectric signal (MES) segmentation and classification is proposed. The classical moving average technique augmented with Principal Components Analysis (PCA), and time-frequency analysis were used for segmentation. Multiresolution Wavelet Analysis (MRWA) was adopted as an effective feature extraction technique while Artificial Neural Networks (ANN) was used for MES classification. Results of classifying four elbow and wrist movements gave 94.9% sensitivity and 94.9% positive predictivity.**
Keywords **Myoelectric signal, classification, wavelet transform, neural networks.**

I. INTRODUCTION

MES are signals recorded using surface electrodes that reflect the localized neuromuscular activity. They have been used in various aspects of medical and biomedical applications [1]. For example, they are used for the diagnosis of neuromuscular diseases such as polymyositics [2]. One of the uses of MES is for controlling prosthesis manipulators [3]. Each MES, generated by muscle in performing different tasks, has a unique pattern. This pattern contains information about the direction of movements and speed of action. To be able to control prosthesis successfully, accurate segmentation and classification of these patterns is essential [4]. Furthermore, fast response of the prosthesis is needed which limits the period over which these features can be extracted. Hudgin et al. (1993) segmented the MES signal and represented each by a set of simple time-domain features. A standard ANN was trained to classify four arm movements [4]. Other feature extraction methods based on frequency analysis were also used [5]. However, MES signals are nonstationary and have highly complex time-frequency characteristics. Consequently, these signals can not be analyzed using classical methods such as Fourier transform. Although the Short-time Fourier Transform can be used to satisfy the stationarity condition for such nonstationary signals, it suffers from the fact that the performance depends on choosing an appropriate length of the desired segment of the signal. To overcome such problem, Wavelet Transform (WT) was used as a feature extraction method and has been widely used in signal and image analysis including [6-8]. WT was also used for MES signal classification [6]. However, despite the fact that not all wavelet coefficients were used to create the features input set, still large number of wavelet coefficients was used. That resulted in having an ANN classifier with a large number of free parameters.

The control signal for a prosthesis device can be derived from a single or multiple MES channels. Using a single channel would result in a less complex input structure to the classifier. However, using multi-channel signals makes the positions of the electrodes on the human subject become less critical to the experiment and increase the classification accuracy [9].

In this research, MES data from the arm biceps and triceps was collected for elbow and wrist movements. The classical Moving Average (MA) together with PCA and wavelets were utilized for movement segmentation. The striking features belonging to different signals classes can be obtained by transforming the data space into a reduced feature space that retains most of the intrinsic information content of the data. MRWA was used to derive distinct set of wavelets coefficients for each MES signal pattern. A reduced set of wavelets coefficients was then obtained to provide a way to reduce the number of free parameters of the neural network classifier.

II. METHODOLOGY

Myoelectric signals were collected from biceps and triceps branchii since these muscle groups are directly responsible for the elbow and wrist movements of interest [10]. Four differential myoelectric signal channels were recorded using surface electrodes. Two channels were used to record potentials from the biceps and two channels recorded the triceps activity. Since the types of contraction of interest are grouped into elbow and wrist movements, the human subject was asked to produce a number of continuous sets of movements which contained either alternating elbow flexion and extension or alternating wrist pronation and supination. Fig.1 shows an example of MES for a number of elbow flexion and extension movements. The MES analysis needed for prosthesis control is composed of segmentation and classification. The segmentation process is accomplished through subjecting the MES signals to the following stages: squaring, moving average, PCA and wavelet transform. One channel of the biceps MES is squared not only to enhance the contrast between the background noise and transient MES activities but also between MES activities themselves. Furthermore, the squared signal is conditioned for the next MA stage.

Report Documentation Page

Report Date	Report Type	Dates Covered (from... to)
25 Oct 2001	N/A	-

Title and Subtitle Myoelectric Signal Segmentation and Classification Using Wavelets Based Neural Networks	**Contract Number**
	Grant Number
	Program Element Number
Author(s)	**Project Number**
	Task Number
	Work Unit Number
Performing Organization Name(s) and Address(es) School of Engineering American University of Sharjah P.O. Box 2666 Sharjah, UAE	**Performing Organization Report Number**
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500	**Sponsor/Monitor's Acronym(s)**
	Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited	
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.	
Abstract	
Subject Terms	
Report Classification unclassified	**Classification of this page** unclassified
Classification of Abstract unclassified	**Limitation of Abstract** UU
Number of Pages 4	

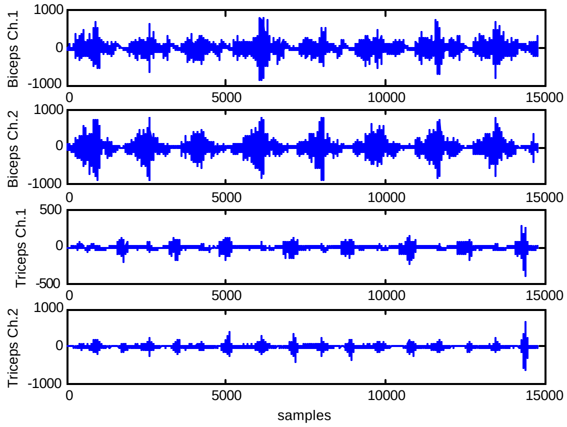

Fig.1: Biceps and triceps MES signals.

The squared MES signal is then filtered using MA method with a window length of 150 samples (at 1kHz sampling rate), as shown in Fig.2. As it can be seen, the MA has a cyclic pattern which represents the arm flexion-extension activity with the minimum of each cycle corresponds to the end of extension segment and the start of the next flexion segment.

To detect the end of the flexion segment, PCA was applied to the four channel signals for each flexion-extension cycle obtained earlier using the MA. PCA consists of finding a linear combination of the original data sequences such that the obtained signals are orthogonal and their variance maximized [11]. This is followed by computing the WT of the absolute value for each eigenvector with 64 different levels of resolution. It was found that the peak value of the WT of the first eigenvector at the middle resolution level coincides with the end of the flexion segment as shown in Fig.3. The index of this peak value is used to locate the end of flexion and the beginning of extension segment. The above segmentation procedure was also successfully used to segment the wrist pronation and supination movements.

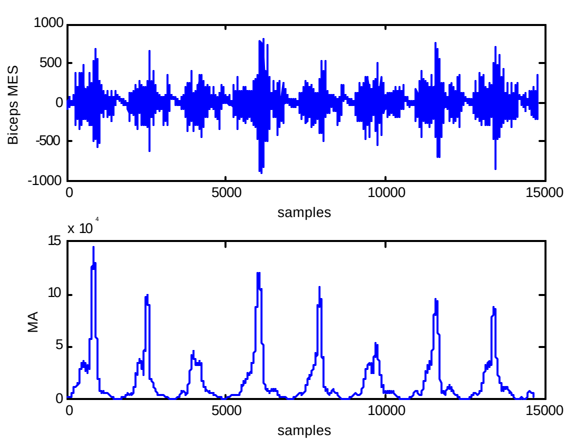

Fig.2: Biceps MES and its MA signals.

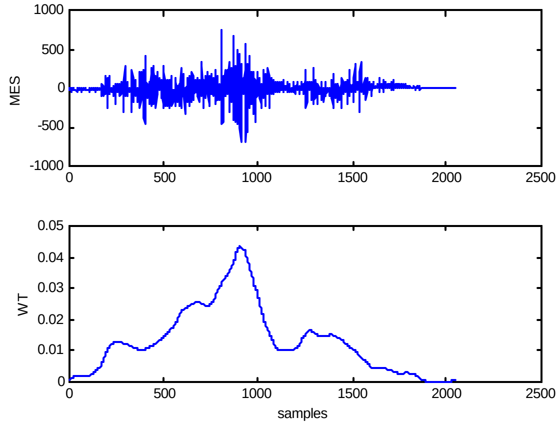

Fig.3: MES and the WT of the first eigenvector at the middle resolution.

Following the segmentation stage, a set of two data segments of 1024 samples each (with zero padding) from two MES channels representing both the biceps and triceps were stored in an array for further signal processing. Each set of segments represents flexion, extension, pronation or supination. MRWA is used to obtain a reduced set of features that retains most of the intrinsic information of the signal and reflects the energy concentration in low and high frequency components [12].

The MRWA decomposition of a signal f(x) can be represented in terms of the superposition of wavelets of different dilations and translations:

$$f(x) = c_{00}\phi_{0,k}(x) + \sum_{j=1}^{\infty}\sum_{k=-\infty}^{\infty} d_{j,k}\psi_{j,k}(x) \qquad (1)$$

where j and k are the scale and time shifts respectively, c_{00} is the last smoothed coefficient to be produced after decomposition, $\{d_{j,k} : j,k \in Z\}$ are the details coefficients of wavelets decomposition, $\phi(x)$ is the scaling function and $\psi(x)$ is the mother wavelet [12]. The WAVELAB software [13] was used to generate the MRWA. Since the objective of this research was to classify arm movements, it is advantageous to perform signal classification using a reduced but representative set of coefficients. For each movement under consideration, the wavelet transform was obtained using all levels of resolution. For example, a 1024 samples segment would produce 10 levels of resolution. At each resolution, the mean of the absolute value of all coefficients was calculated which resulted in a vector containing 10 values. Therefore, if two channels are considered for classification, then a total of 20 feature values are used.

Artificial Neural Networks (ANN) have been widely used for classification purposes due to their trainability and robustness [14]. The backpropogation training algorithm is commonly used to iteratively minimize the following cost function with respect to the interconnection weights and neurons thresholds:

$$E = \frac{1}{2}\sum_{1}^{P}\sum_{k=1}^{N}(d_k - z_k)^2 \qquad (2)$$

Where P is the number of training patterns and N is the number of output nodes. d_k and z_k are the desired and actual responses for output node k, respectively.

Arm movement classification was performed using multilayer feedforward networks with the backpropgation training algorithm. 70% of the data was used for training the network while the rest was used for testing. The Neurosolution software [15] was used for constructing, training and testing the neural network.

III. RESULTS AND DISCUSSION

In this research, MES signal classification using one or two channels was investigated. For a quantitative classifier performance evaluation, segment-by-segment matching between the actual and the corresponding output classification codes was performed. Results of matching are true positive (TP), false positive (FP) or false negative (FN). For a hand movement, X, TP occurs when the classifier code matches that of movement X. FP occurs when the classifier output is the code of movement X while the input is a different movement. FN occurs when the classifier output code is different from that of input movement X.

Consequently, the following two parameters were computed; the sensitivity (Se%) and positive predictivity (+P%), which are defined as:

$$Se\% = \frac{TP}{TP + FN} \times 100\,\% \qquad (3)$$

$$+P\% = \frac{TP}{TP + FP} \times 100\,\% \qquad (4)$$

The sensitivity Se% represents the percentage of movements that were correctly detected while the positive predictivity +P% represents the percentage of movements detected that were correct movements.

Table I shows the movement classification results that were obtained using single or two channels. The average values of Se% = 89.7% and +P% = 93.3% were obtained with a single channel while values of Se% = 94.9% and +P% 94.9% were achieved with two MES channels. These results confirm previous findings that two channels are necessary for improved classification performance regardless of the features extraction method.

TABLE I
MES movement classification performance using a single channel or two channels

Movement	TP 1 /2 Ch.	FP 1 /2 Ch.	FN 1 /2 Ch.
Elbow flexion	21/21	0 /1	0/0
Elbow extension	18/20	0 /1	3 /1
Wrist pronation	15/17	1 /1	3 /1
Wrist supination	16/16	4/1	2/2
Combined	70/74	5/4	8/4

It was also found that lower and higher resolution levels were equally important to achieve adequate classification performance. This was true regardless of whether a single or two channels were considered. This reflects the fact that both low and high frequencies of the MES signals are equally important for classification. Hence, coefficients from all resolutions were used to create the observation features vector. Furthermore, using MRWA to extract MES features resulted in higher classification performance compared with using statistical and temporal features such as mean, zero crossing,..etc. [9] when both methods used neural networks as a classifier.

IV. CONCLUSIONS

Classification of elbow flexion-extension and wrist pronation-supination was investigated. Segmentation using a combination of MA, PCA and WT was used. MRWA was adopted as an effective feature extraction technique while ANN used for MES classification. The use of multiple channels was found to improve classification performance. Results of classifying the four movements gave 94.9% sensitivity and 94.9% positive predictivity. Future work concentrates on applying this method on more subjects and extending this work to prosthesis control.

ACKNOWLEDGMENT

The authors would like to thank Dr. Ali Zalzala from the Electrical and Computer Engineering Department at Herwit Watt University - Scotland for providing the MES data and the valuable discussion about this work.

REFERENCES.

[1] B. Hudgins, K. Englehart, P. Parker and R. Scott, **A microprocessor based multifunction Myoelectric control system**, *23rd Canadian Medical and Biological Engineering Society Conference*, Toronto, May 1997.

[2] N. Kumaravel, and V. Kavitha, **Automatic diagnosis of neuro-muscular diseases using neural network**, *Biomedical Sciences Instrumentation*, 30, 245-250, 1994.

[3] R. Scott, and P. Parker, **Myoelectric prostheses: State of the art**, *Journal of Medical Engineering & Technology*, 12(4), 143-151, 1988.
[4] B. Hudgins, P. Parker and R. Scott, **A new strategy for multifunction myoelectric control,** *IEEE Transactions on Biomedical Engineering*, 40(1), 82-94, 1993.
[5] K. Katutoshi, O. Koji and T. Takao, **A discrimination system using neural networks for EMG-controlled prostheses**, *Proceedings of IEEE Int. Workshop Robot Human Commun.*, Tokyo, Japan, pp.69-74, 1992.
[6] K. Englehart, B. Hudgins, P. Parker and M. Stevenson, **Classification of the Myoelectric Signal using Time-Frequency Based Representations**, *Medical Engineering and Physics, Special Issue: Intelligent Data Analysis in Electromyography and Electroneurography*, Vol. 21, pp. 431-438, 1999.
[7] D. Donoho and I. Johnstone, **Adapting to unknown smoothness via wavelet shrinkage**, *Technical report, Department of Statistics, Stanford University*, 1993.
[8] E. Majani **Biorthogonal wavelets for image compression,** *Proc. Of the SPIE*, VCIP'94, 1994.
[9] U. Kuruganti, B. Hudgins and R. Scott**, Two-channel enhancement of a multifunction control system,** *IEEE Transactions on Biomedical Engineering*, 42(1), 109-111, 1995.
[10] A. Zalzala and N. Chiyaratana**, Myoelectric signal Classification using evolutionary Hybrid RBF-MLP Networks,** *Proc. of the 2000 Congress on Evolutionary Computation*, NJ, p. 691-698, 2000.
[11] E. Oja (ed.), **Subspace methods of pattern recognition,** *research studies press*, Letchworth, U.K, 1983.
[12] S. Mallat and S. Zhong, **Characterization of signals fro multiscale edges,** *IEEE Trans. Pattern Anal. Machine Intell.*, Vol. 14, pp. 710-732, 1992.
[13] D. Donoho, X. Huo, and T. Yu, **Wavelab Software,** Stanford University, http://www-stat.stanford.edu/~wavelab, 1999.
[14] U. Halici, A. Erol, and G. Ongun, **Industrial applications of Hierarchical neural networks: Character recognition and finger print classification,** *in industrial applications of neural networks, The CRC Press, International Series on Computational intelligence*, 1999.
[15] Neurosolution software**, Neural Network software,** by NeuroDimension, Inc, http://www.nd.com, 2000.