SEMG CLASSIFICATION FOR UPPER-LIMB PROSTHESIS CONTROL USING HIGHER ORDER STATISTICS

Alireza Khadivi[1], Kianoush Nazarpour[2], Hamid Soltanain Zadeh[1]

[1] Department of Electrical and Computer Engineering, Faculty of Engineering, University of Tehran, Tehran, Iran
[2] Department of Biomedical Engineering, Faculty of Engineering, Tarbiat Modarres University, Tehran, Iran

ABSTRACT

The aim of this paper is to present application of higher order statistics for Surface Electromyogram (sEMG) signal pattern classification. The new pattern recognition algorithm exploits a multilayer perceptron (MLP) as the classifier and the feature vector is a combination of cumulants of the second-, third- and fourth- orders and Integral of Absolute (IAV) of two channel sEMG stationary segments. The detected sEMG signals are used in classifying four upper-limb primitive motions, namely, elbow flexion (F), elbow extension (E), wrist supination (S) and wrist pronation (P). The simulation results illustrate the considerable accuracy of the proposed framework in sEMG pattern recognition.

1. INTRODUCTION

The Surface Electromyogram signal is the electric manifestation of neuromuscular activity [1] and is collected non-invasively on the skin by the means of appropriate electrodes [2]. It is a stochastic complex signal that depends on anatomical and physiological properties of the contracting muscle [1]. Due to characteristics of sEMG it is well established that sEMG recordings from an amputee's residual muscles can be used to control prosthesis movement. The control strategy is based on sEMG pattern classification detected during muscular contraction. Lots of researchers have made attempts to present new methods of sEMG processing such as AR Modeling [3]-[5], Statistical Pattern Recognition techniques [6], Discrete Wavelet Transform [7] and Artificial Neural Networks [8]-[10].

Design of sEMG pattern recognition system consists of several stages, sEMG detection, formation of the motion classes, feature extraction, developing classification algorithm and estimation of the classification error. The authors believe that the most critical point is the extraction of effective features from sEMG signal, while the classification performance is more profoundly affected by the choice of features [11]. This investigation explores pattern recognition of sEMG signals produced by biceps brachii and triceps brachii muscles to identify four motions, namely, elbow flexion, elbow extension, wrist supination and wrist pronation.

The motivation behind this study is to exploit higher order statistics in sEMG feature extraction in a two channel sEMG signal motion classification problem. During the past years there has been an everyday increasing application for higher order statistics. Adaptive filtering, blind equalization, biomedical signal processing and many other research areas have been gained from higher order statistics. These statistics are dramatically capable in solving problems where the interested signal is non-Gaussian and corrupted by Gaussian measurement noise, while there are blind to any kind of a Gaussian process [11]. In the past decade due to shortage of analytical tools, the sEMG signal was treated to be Gaussian. Assuming semi-Gaussianity for sEMG leads us to use higher order statistics.

In order to elaborate capability of cumulants based features we have performed two experiments. In the first one we have merely introduced the IAV feature of sEMG signal to the classifier. Secondly, the above experiment has been done when the input feature vector consists of IAV and the cumulants of the second-, third- and fourth-orders of sEMG signal. Although the calculation of cumulants based features increases computational complexity, significant advances in sEMG pattern classification has been achieved.

2. METHOD

In the following, we first introduce the sEMG detection setup and experimental procedure. Next we propose the higher order statistics in sEMG pattern classification. Then the MLP neural network, based on BFGS learning algorithm, will be explored.

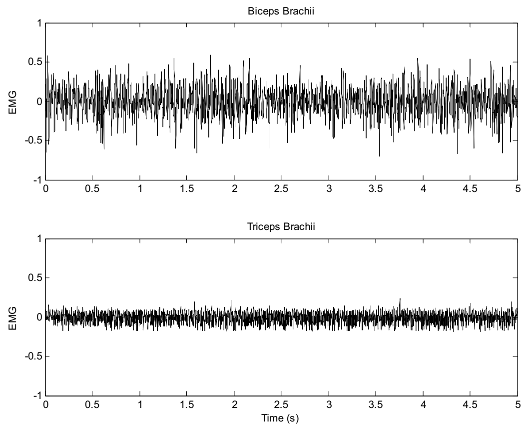

Figure 1. A sample detected sEMG signal from biceps and triceps during Flexion LOW.

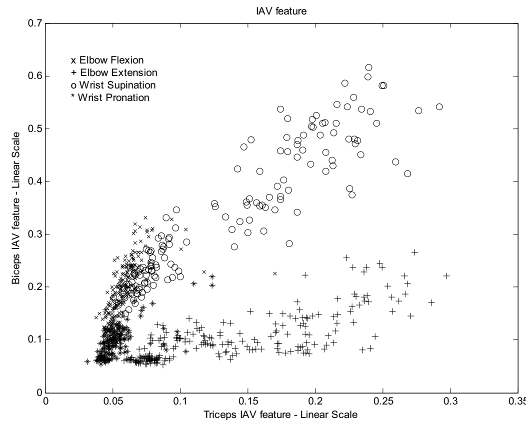

Figure 2. Feature space of IAV feature on linear scale, for biceps and triceps sEMG's for four motions in all three contraction states.

2.1. sEMG detection System

The sEMG signals were picked up from biceps brachii and triceps brachii of a healthy 24 years man by two pairs of Ag/AgCl electrodes**.** Each of the electrodes in a pair was separated from the other by 20mm. The sEMG signal was amplified and band-pass filtered. A 50Hz notch filter then applied to the detected signal Sampling rate was set at 1000 using a home made 12 bit A/D converter board. The main parameters of system is as follows,

The input impedance: $100\,\mathrm{M\Omega}$;
The common mode rejection ratio: > 90dB;
The amplification scale: 10~20,000.

The man was asked to actuate HIGH, MED and LOW contraction each of the biceps and triceps muscles. HIGH, MED and LOW were defined as 90%, 50% and 10% of the MVC (Maximum Voluntary Contraction), respectively. Continuous recordings were made from both muscles for the 5s periods. Each record subdivided into 200ms segments, yielding 25 stationary time series per contraction which were then used for the signal pattern recognition. The subject did the experiment three times for each level of contraction. Fig. 1 shows a sample of sEMG signal from biceps and triceps during Flexion LOW.

2.2. sEMG Feature Extraction

Conventionally, sEMG signal classification has been performed by introducing time domain features as input to the classifier. The most popular applicable features that have been extracted in time domain are IAV, WAMP Wilson Amplitude), HIST (Histogram) and AR coefficients [6]. The most challenging problem of these approaches is that the classification rate is low, and they are not robust to measurement noises due to motion artifacts and also instrumentation amplifier interference [6].

Following is the description of the most frequently used sEMG feature, IAV, plus one newly proposed feature which all investigated for this research.

IAV of sEMG signal *x(t)* is calculated as

$$\mathrm{IAV} = \frac{1}{N}\sum_{i=1}^{N}\left|x_i\right| \tag{1}$$

Fig. 2 shows the IAV feature space of the set sEMG signal that detected for this paper. As it is shown the four motions clusters are not completely distinct.

Our solution to overcome this problem is to use Higher Order Statistics. Three types of statistics known as second-, third-, and forth order cumulants, have been derived over stationary segments of sEMG signal as statistical features. Assuming zero mean time series segments, these features can be determined as follows [11]:

$$C_{2,x}(\tau_1) = E\{x(t)x(t+\tau_1)\} \tag{2}$$

$$C_{3,x}(\tau_1,\tau_2) = E\{x(t)x(t+\tau_1)x(t+\tau_2)\} \tag{3}$$

$$\begin{aligned} C_{4,x}(\tau_1,\tau_2,\tau_3) = {} & E\{x(t)x(t+\tau_1)x(t+\tau_2)x(t+\tau_3)\} \\ & - C_{2,x}(\tau_1)C_{2,x}(\tau_2-\tau_3) \\ & - C_{2,x}(\tau_2)C_{2,x}(\tau_3-\tau_1) \\ & - C_{2,x}(\tau_3)C_{2,x}(\tau_1-\tau_2) \end{aligned} \tag{4}$$

where C and τ stand for Cumulant and Time lag, respectively. The curves presented in Fig. 3, show the characteristics of second-, third-, and fourth- order cumulants of sEMG signal detected from biceps and triceps versus time lag during experiment with 10% of MVC (τ_2 and are considered fixed for third- and fourth order cumulants). The variance of the IAV feature vector due to normalized sEMG signal recoded during flexion LOW are 2.9×10^{-4} and 1.5×10^{-5} for biceps and triceps.

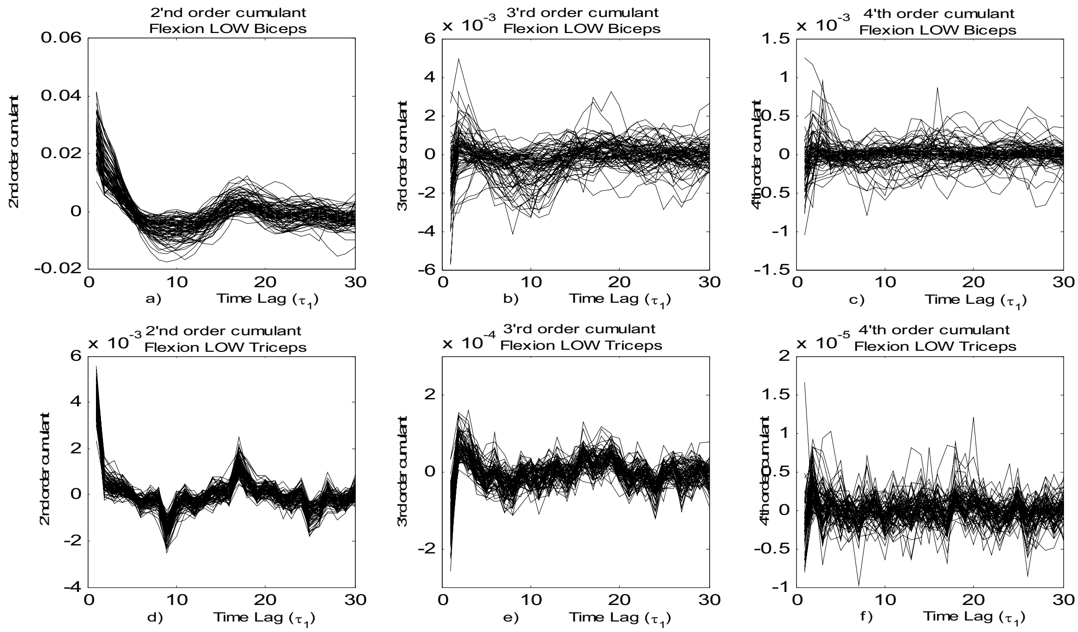

Figure 3. Characteristics of second-, third-, and fourth order cumulants of sEMG signal detected from biceps and triceps versus time lag during experiment with 10% of MVC (τ_2 and τ_3 are considered fixed), a to f.

These values are 0.0011, 7.4×10^{-5} for second-order, 3.3×10^{-5} , 1.02×10^{-6} for third-order. The variances for forth-order cumulants are 8.8×10^{-6}, 2×10^{-8}, respectively. Obviously, using statistical characterization decreases variation among different signals in the same class which enables us to classify the patterns more efficiently.

2. 3. sEMG Pattern Classification

The multilayer perceptron (MLP) is characterized by a set of input units, a layer of output units and a number of hidden layers. Each input unit is connected to each unit in the hidden layer in a feedforward fashion. Each hidden unit is connected to the neurons in the succeeding layer, be it hidden or output, in a similar way. The input to each unit is given by the summation of all of the individual weighted outputs passed from the previous layer. The output is then a function of the summation of these inputs.

The most important factor in the MLP structure selection is the choice of the number of the hidden neurons. This has been done in our work by trial and error. Different MLP networks have been trained and the one of the smallest number of hidden neurons, allowing the classification rate to an acceptable level, has been picked up.

The weights are tuned during the learning period of the network using the gradient method and backpropagation algorithm for gradient generation. In the gradient methods of learning, the weights are updated in each epoch according to the information of gradient of the error surface by:

$$x_{k+1} = x_k + \eta A_k \qquad (5)$$

where η -the learning coefficient- is computed at each epoch and is the direction vector of minimization in k th epoch. In realization of the training algorithm, we have exploited Quasi-Newton Broyden–Fletcher–Goldfarb–Shanno (BFGS) algorithm which is one of most successful ones in the published studies, in which

$$A_k = -H_k^{-1} g_k \qquad (6)$$

with H_k is the approximated Hessian matrix and g_k is the gradient vector of the error function , in the k th epoch.

The network training is accomplished by varying the connection weights and the neuron threshold values using the BFGS algorithm. In the first study, the MLP is a three-layer network, with 2, 4, 4 neurons for input, hidden and output layers, respectively. The input feature vector is the IAV the sEMG detected from biceps and triceps. In the second study, the MLP is an also three-layer network, but 32, 20, 4 neurons for input, hidden and output layers, respectively. The input feature vector is the cumulant based features of the signal. The hidden and output neurons are characterized by a sigmoidal activation function. The input feature vector consists of 5 points representing each cumulant (second-, third-, and forth order) for each recording channel and two IAV values corresponding to biceps and triceps muscles.

Table I. sEMG pattern recognition ratio. All the values are in [%].

Type	IAV %		HOS +IAV	
	Training	Testing	Training	Testing
Flexion	87.80	87.06	90.55	90.20
Extension	99.45	99.33	99.40	98.40
Supination	67.92	63.67	94.40	89.40
Pronation	82.40	75.60	84.48	84.80
Total	84.89	81.41	92.20	90.70

The input feature vector is normalized with respect to the maximum absolute value of the vector. As a result the absolute values of the elements of the input vector are within the range of zero to unity.

3. NUMERICAL RESULTS

Two feature vectors (IAV and IAV-HOS feature) of each channel have been computed to train the MLP, for the purpose of classification. After training, the MLP has been tested by both of the testing and training data. Table I illustrates the classification results.

In Table I, we note that the average rates of correct classification are 81.41% and 90.70% for IAV and for HOS+IAV methods, respectively. This is comparable with other methods in [9] and [12]. In [9], correct classification rates of 88% to 98% was achieved using various neural network architectures such as MLP, Conic Section Function Neural Network (CSFNN), and Fuzzy Clustering Neural Network (FCNN) in conjunction with autoregressive (AR) coefficients as feature. In [12], the highest rate of correct classification is 93.7% using a wavelet-based feature set.

4. CONCLUSION

Following the idea of exploiting HOS in sEMG pattern recognition, n this paper the comparative performance of IAV feature and cumulant-based features have been investigated. Although the results show the capability and efficiency of the proposed algorithm in sEMG pattern classification at the expense of computational complexity, the cumulants adopted in this work are still ad hoc.

Future works may involve a detailed approach to choosing the time lag for the cumulants and analyzing the training behavior of the neural network when dealing with the Higher Order Statistics, in more depth.

5. ACKNOWLEDGMENT

The authors are grateful to Associate Professor S. M. Firoozabadi for his advices, and the signal he donated us.

6. REFERENCES

[1] C. J. De Luca, "Physiology and Mathematics of Myoelectric Signal," *IEEE Trans. Biomed. Eng.*, vol. BME-26, pp. 313-325, 1979.

[2] R. Merletti, D. Farina, A. Granata, "Non-Invasive Assessment of Motor Unit Properties with Linear Electrode Arrays," *Jour. Electroencephalogr. Clin. Neurophysiol.* vol. 50, pp. 524-540.

[3] D. Graupe and K. W. Cline, "Functional Separation of EMG Signal via ARMA Identification Methods for Prosthetic Control Purpose," *IEEE Trans. Sys. Man and Cyber.*, vol. SMC-5, no. 2, pp. 252-259, 1975.

[4] T. Kiryu, C. J. De Luca, and Y. Saitoh, "AR Modeling of Myoelectric Interference Signal During a Ramp Contraction," *IEEE Trans. Biomed. Eng.*, vol. 41, pp. 1031-1038, Nov. 1994.

[5] R. G. Triolo, D. H. Nash, and J. D. Moskowitz, "The Identification of Time Series Model of Lower Extremity EMG for the Control of Prostheses Using Box-Jenkins Criteria," *IEEE Trans. Biomed. Eng.,* vol. 35, no. 8, pp. 584-594, Aug. 1988.

[6] M. Z. Kermani, B. C. Wheeler, K. Badie, R. M. Hashemi, "EMG Feature Evaluation for Movement Control of Upper Extremity Prostheses," *IEEE Trans. Rehab. Eng.*, vol. 3, no. 4, pp. 324-333, Dec. 1995.

[7] K. Englehart, "Signal Representation for Classification of the Transient Myoelectric Signal," Ph.D. Dissertation, Univ. New Brunswick, Fredericton, NB, Canada, 1998.

[8] M. Kelly and P. Parker, "Application of Neural Network to Myoelectric Signal Analysis: A Preliminary Study," *IEEE Trans. Biomed. Eng.*, vol. 37, no. 3, pp. 221-230, Mar. 1990.

[9] B. Karlik, M. O. Tokhi, M. Alci, "A Fuzzy Clustering Neural Network Architecture for Multifunctional Upper-Limb Prosthesis," *IEEE Trans. Biomed. Eng.*, vol. 50, no. 11, Nov. 2003.

[10] F. H. Y. Chan, Y. Yang, F. K. Lam, Y. Zhang, P. A. Parker, "Fuzzy EMG Classification for Prosthesis Control," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 3, pp. 305-311, Sep. 2000.

[11] J. M. Mendel, "Tutorial on Higher-Order Statistics (Spectra) in Signal Processing and System Theory: Theoretical Results and Some Applications," *Proceeding of IEEE*, vol. 49, no. 30, Mar. 1991.

[12] K. Englehart, B. Hudgins, P. A. Parker, and M. Stevenson, "Classification of the myoelectric signal using time-frequency based representations," *Med. Eng. Phys. (Special Issue on Intel. Data Anal. Electromyogr. Electroneurogr.)*, vol. 21, pp. 431-438, 1999.