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Procedia Computer Science 49 (2015) 58 – 65

Procedia Computer Science

ICAC3'15

Hand Motion Recognition From Single Channel Surface EMG Using Wavelet & Artificial Neural Network

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Abstract

The strength of the muscle contraction can be easily measured by the muscle activity extracted at the skin surface. Analysis of surface Electromyogram (sEMG) is one of the standard procedures to identify posture, gesture and actions (i.e. control of prosthesis via learnt body actions). sEMG signals are usually complex in nature. It can be easily classified into differentiated muscular activities with appropriate signal processing tools. In order to analyze its complexity, various studies have been carried out but have proved unsuccessful, due to huge differences in muscular activities of some muscles over the other. This paper presents a new technique to identify low level hand movement by classifying the single channel sEMG. Single channel sEMG analysis is preferred over multi-channel due to its simplicity, computational cost and efficiency. Wavelet transformation and artificial neural network (ANN) classifier are utilized to classify and analyze the sEMG signal in a better way.

Peer-review under responsibility of organizing committee of the 4th International Conference on Advances in Computing, Communication and Control (ICAC3'15)

Keywords: sEMG, ANN, wavelet.;

1. Introduction

Wide applications of EMG signals are reported in literature such as diagnosis of prosthetic/orthotic devices, rehabilitation, diagnostic evaluation of muscle and nerve disorders, human- computer interfaces (HCI), Wheel chair handling[1,2]. Classification of hand movements by the help of sEMG signals find wide range of application such as controlling of prosthetic hands, human computer interface(HCI) and rehabilitation robots etc[4,5,6]. In order to get high classification rates there are several methods and algorithms have been developed such as ANNs[3], fuzzy classifiers, neuro-fuzzy classifiers[4] and other probabilistic based methods[5].

Complexity of noise in EMG signal is more than other biosignals. Sources of noise are motion artifacts, built-in equipment, electromagnetic radiation, etc[3]. Multiclass classification from sEMG is even more difficult[2]. The

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Peer-review under responsibility of organizing committee of the 4th International Conference on Advances in Computing, Communication and Control (ICAC3'15)
doi:10.1016/j.procs.2015.04.227

nature of EMG signal is complex and highly nonlinear that makes it difficult to have a explicit relation between the measured signals and a motion command.To distinguish and identify the functionality of different sEMG signals from their extracted features, pattern recognition techniques are very important. Most of the research work has been done with multichannel EMG[6]. Multichannel EMG signals increases the efficiency of motion classification. Some of the previous studies like[7,8] shows that multichannel is advantageous. As number of channels increases average classification accuracy will increase but handling a large data set of features becomes complicated after the numbers of channels more than four[9]. Multichannel system of EMG is advantageous for classification but it makes system complex and bulky. A novel technique of identifying the finger actions using a single channel sEMG is demonstrated in[10]. To overcome the limitations of the multichannel sEMG based systems, single channel system approach is used. While some researchers have reported the use of single channel sEMG classification, the difficulty related to such methods is the poor reliability. The challenge in such systems is the very low level of contraction (flexion) and the close proximity of the related muscles resulting in the most pronounced challenge being the very low signal to noise ratio (SNR) and cross talk.

Feature extraction and feature classification are two important tasks after sEMG data acquisition. The wavelet transform, a multi-resolution time-frequency analysis, is preferred for EMG analysis[11,12]. The robustness of the wavelet domain method proposed in[11] depends on the feature dimension. There are different machine learning methods found in literature, ANN is one of them. ANN has many remarkable characteristics which makes it highly efficient for non-linear processing. Some of these characteristics are highly parallel processing capacity, robustness to noise and fault, also its ability to learn and generalize the pattern[13]. ANN is used in some of the popular areas of application such as forecasting cascade failure[14], image processing[15], detection of neuromuscular disorders[16].

Single channel sEMG is used in this paper to classify three different hand movements. Wavelet transformation on data set is performed. It increases feature space of data set so that classification can be done effectively. Artificial Neural Network (ANN) is used for classification of the data set to increase classification efficiency and reliability of the single channel method. The paper is organized as follows. Section II gives methodology of data acquisition; feature extraction and feature classification is explained. Section III explains experimental results and Section IV describes data analysis using ANN. Section V is about conclusion.

2. Methodology

Single channel data is acquired from National Instrument Hardware. Appropriate signal processing was performed to get feature sets and using those features classification was done. Fig. 1 shows the flow of the work done.

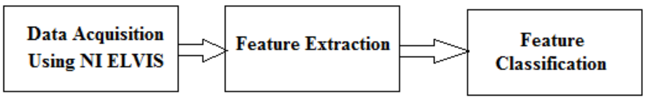

Fig. 1. Methodology

2.1. Data Acquisition

Single channel data acquisition board of National Instrument (NI) is used to acquire surface EMG signals for hand motions. The National Instruments Educational Laboratory Virtual Instrumentation Suite (NI ELVIS) with QNET module for electromyography is used to acquire three different hand motions of four healthy person. NI ELVIS is a hands-on design and prototyping platform that integrates the 12 most commonly used instruments including oscilloscope, digital multimeter, function generator, bodeanalyzer, and more into a compact form factor ideal for the lab or classroom.

The Quanser Engineering Trainers for NI ELVIS used for implementation and application of biomedical using principles of electromyography (EMG). This platform is useful to do experimentation of signal processing and control engineering. The board is equipped with a PWM servo motor with built-in power amplifier and “gripper”for simulating a prosthetic actuator. Delysis parallel bar differential electrodes with fixed inter electrode distance of 10 mm, inbuilt band pass filter of pass band of 20Hz to 450 Hz and gain of 1000 were used as electrode in this paper.

Fig. 2. Hardware setup

2.2. Feature Extraction

Feature extraction attempts to extract usable information from the sEMG through development of feature sets which are chosen in such a way that they preserve class separability [17]. The firing rate affects the frequency components of sEMG. Only spectral analysis of sEMG does not provide enough information, to distinguish between changes in the spectral content of the signal which may be due to change in the rate of activity or due to the other parameters. Wavelet based feature set gives more celerity than time domain based methods (RMS, Mean SD, etc) and Fourier Transforms [12].

Discrete wavelet transform (DWT) is used in this study. DWT transforms interested signal into multi-resolution subsets of coefficients. Transformation of signal is done with suitable choice of wavelet basis function (WF) also called as mother wavelet. WF plays a important role in the multi-resolution analysis depending on applications. The DWT of a signal $x(n)$ is obtained as

$$C(a, b) = \sum_{n \in Z} x[n]\psi_{a,b}[n] \tag{1}$$

where a is the dilation or scale, b the translation and $\psi_{a,b}[n]$ is the discrete wavelet basis function which is expressed as

$$\psi_{a,b}[n] = \left(\frac{1}{\sqrt{a}}\right) \times \psi\left(\frac{n-b}{a}\right) \tag{2}$$

DWT use high-pass filter to obtain high frequency components so-called details coefficient (D) and low-pass filter to obtain low frequency components so-called approximations coefficients (A. Different mother wavelets (Daubechies wavelet (db2 and db7), the forth and the fifth orders of Coiflet wavelet (coif4 and coif5), the fifth order of Symlets wavelet (sym5), the fifth order of BioSpline wavelet (bior5.5)) were used to get detail coefficients upto four level of decomposition of sEMG [18]. It is seen that classification performance obtained from wavelet decomposition using BioSpline 5.5 for first three levels is greater than the classification performance obtained in 4th level.The coefficients of significant magnitude are identified by applying a threshold. It is found that the coefficients of level one are of significant magnitude and hence considered for the further analysis. After applying the DWT on EMG signals number of local maxima (N) are calculated for details coefficients of first level. Mean (μ) of all local maxima is calculated. Let mi be the local maxima.

$$\mu = \frac{\sum_{i=0}^{i=N} m_i}{N} \tag{3}$$

The maximum of the all local maxima verses is used as a features of sEMG and was classified using ANN to identify the associated actions.

2.3. Feature classification

Feature classification is done by artificial neural network(ANN). Artificial neural network is a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs[9]. ANN consist of different layer input layer, hidden layer and output layer. 3 shows basic ANN feedforward model. These are made up of interconnected nodes which is consist of activation function. Crucial element in modelling neural network is selecting an appropriate number of hidden neurons for good performance. Large number of hidden neurons may cause overfitting, while small number may causes insufficient learning[17]. Crucial element in modelling neural network is selecting an appropriate number of hidden neurons for good performance. Large number of hidden neurons may cause overfitting, while small number may causes insufficient learning.

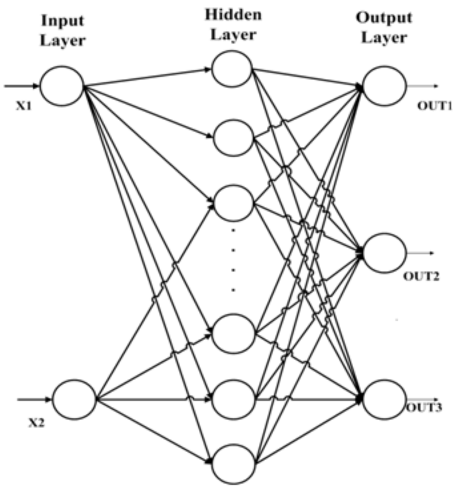

Fig. 3. Feed Forward Network

3. Experiment

Four volunteers (three males and one female) helped in taking readings of EMG signal from hand movement. Before connecting any electrode to the hand, for conducting any experiment and taking reading the skin was prepared by shaving off hair, exfoliated and finally cleaned by 70 % v/v alcohol swab.The Flexor Digitorum superficialis (FDS) muscle is highly compartmentalized i.e. various wrist movement resides indifferent zones within the same muscle. Hence electrode is connected to this muscle, and sEMG was recorded at the sampling rate of 1000 samples per second. Fig.2 shows the setup for experimentation. Typically, here three different movements are taken, closed palm, open palm and wrist extension. Reading was taken for 5 seconds for each movement. After each movement 2 seconds is kept as rest period. This procedure is repeated for 90 seconds for each volunteer. Sample of raw sEMG recorded from one subject and for all three classes is shown in the Fig.4.

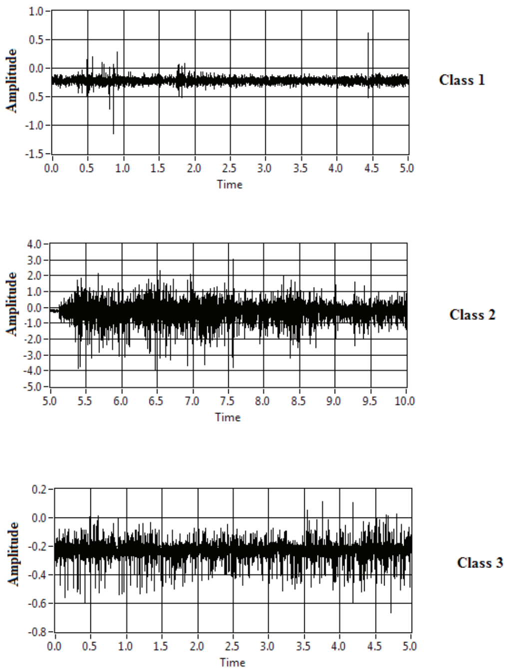

Fig. 4. Raw sEMG of one of the subject

Class 1: Open Palm.
Class 2: Closed Palm.
Class 3: Wrist Extension.

4. Data Analysis And Results

The first step of the analysis of the data involved segmentation of raw sEMG into 1s long segments for each class. This resulted in 50 segments for each of the four classes and for each subject. The recordings were analyzed using wavelet maxima technique described earlier. The features were plotted in the two-dimensional feature space to visually identify the formation of clusters representing each action. Results are shown in figure Fig.5.

The ANN architecture considered for this study comprises of 3 layer feed forward network with 2 inputs neurons, ten neurons in hidden layer and 3 output neurons. Sigmoid activation function is used for all these neurons. ANN analysis was done with MATLAB neural network toolbox. Training of network is performed using 200 data sets for individual hand movements. Each set consists of mean of maxima and amplitude of wavelet coefficients as input feature vector obtained from specific type of hand movement. To minimize mean square error (MES) while training the weights and biases of the network were iteratively adjusted using Back-propagation learning. It improves the rate of network performance.

Two of the important parameters of ANN, lambda and sigma vary between 0 to 1. Its effect on accuracy of an ANN model is observed. Figure Fig.6,7 shows accuracy graph for different values of lambda and sigma for data of subject 1. From figures it is seen that maximum accuracy obtained at 0.005 values of lambda and sigma. Confusion matrix is calculated from these estimated values of lambda and sigma which is shown in figure 8. In the pattern recognition applications, confusion matrix is known as one of the most useful tool. It is employed for distinction among assorted hand movements for all subjects. It has ability to verify if the system with confusing two classes. Figure 8 depicts our

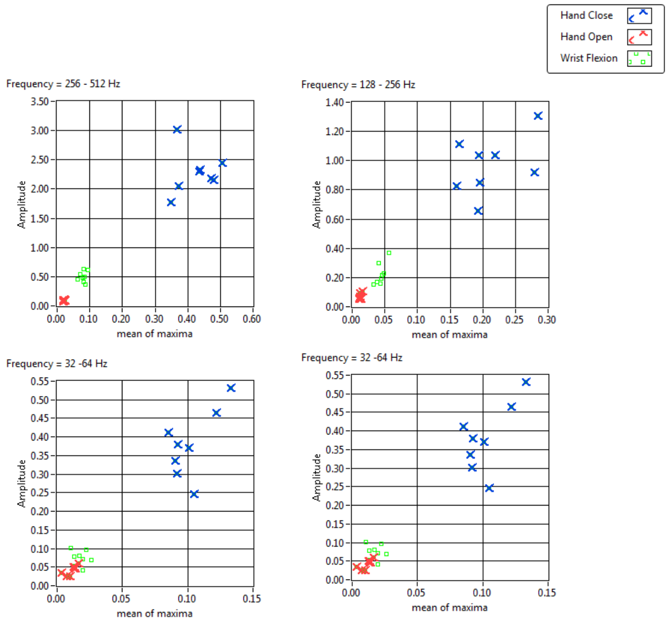

Fig. 5. Feature extraction

results for this study. Each column of the matrix represents the instances in an actual class, while each row represents the instances in a predicted class. Results show a minimum class based recognition rate of 98.4% while a maximum error rate of 1.6% depicting class confusion was recorded.

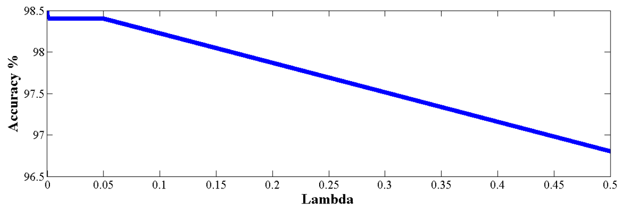

Fig. 6. Lambda vs accuracy

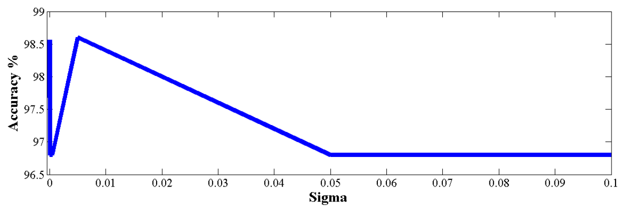

Fig. 7. Sigma vs accuracy

ANN gives better results for single channel sEMG classification. Results acquired from simple feed forward ANN network are presented in table 4. From the table it is observed that palm open movement detected with 100% accuracy for all subject. Palm closed movement and wrist extension also gives sufficient accuracy. Based on these results average recognition rate of 93.25% was obtained by the proposed methodology using ANN.

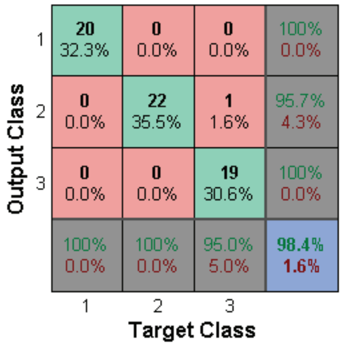

Fig. 8. Confusion matrix for one male subject

Table 1. Statistical overview of rate of success of the real-time ANN system for sEMG pattern discrimination system.

	Movements			
Subjects	**Opening**	**Closing**	**Wrist Extension**	**Average Results**
Subject1	100%	87.5%	88.9%	92%
Subject2	100%	95.7%	100%	98.6%
Subject3	100%	93.3%	78.9%	90.7%
Subject4	100%	83.3%	92.7%	91.7%
Average Results	100%	89.95%	90.1%	93.25%

5. Conclusion

sEMG provides a non-invasive tool to give reference control signals for prosthetic hands. It was shown that single channel signal is sufficient to identify three basic hand movements which reduces the cost of overall system. Wavelet analysis gives information in time-frequency domain which is suitable for sEMG feature extraction. ANN based learning method is a practical candidate in the sEMG feature classification system. Future work is aimed at augmenting sEMG signals for real- time prosthetic arm control.

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