NON INVASIVE TECHNIQUE BASED EVALUATION OF ELECTROMYOGRAM SIGNALS USING STATISTICAL ALGORITHM

Tanu Sharma[1], Karan Veer[2], Ravinder Agarwal[2]
[1]CSED Department, Global college of Engineering, Khanpur Kuhi
[2]EIED Department, THAPAR University, Patiala

Abstract

It is well known that Surface Electromyography is the activity that is being generated when voluntary contraction took place, so in this investigation, the study of Surface Electromyogram (SEMG) signals at different above-elbow muscles were carried out. These signals were easily acquired from surface of skin of the body using non-invasively house design of hardware system and various techniques for the interpretation of these recorded signals using one way repeated factorial analysis of variance were presented. Acquired data from selected locations of above elbow was interpreted for various features using LABVIEW soft scope and finally the computations of parameters were done. Result shows characteristics change in extracted feature values for different movements with respect to each position and movement.

Keywords: Electromyogram signal, data acquisition, electrode, statistical technique

1. INTRODUCTION

Electromyogram (EMG) signal is a measure of electrical currents generated in muscle for measuring its responses. The nervous system controls the muscle activity i.e. contraction or relaxation of muscle. Because of its random nature, signal is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. Surface Electromyogram sensor at the surface of the skin collects signals from different motor units at a time generated due to interaction of different action potential signals. Due to the complexity of Surface Electromyogram signal, powerful and advance methodologies of analysis are becoming a very important requirement in biomedical engineering [1-2].

The myoelectric signals are used in reference to skeletal muscles that control movements. Physiological factors vary independently among different muscles in the body. Few of factors that influence the processed Surface Electromyogram signal have been classified [3]. These signals are detected by placing three electrodes on the skin surface. Two electrodes are positioned to measure differential voltage between them when a myoelectric signal occurs. The third electrode is placed in a neutral area and its output is used to cancel the noise that can otherwise interfere with the signals from the other two electrodes [4]. The myoelectric signal is used in many clinical applications for rehabilitation point of view has been recognized as efficient source for human- machine interface [5].

Electromyography provides easy access to physiological processes that cause the muscle to generate force, produce movement and accomplish the countless functions to interact with the world around us. It provides many important signals which are still to be understood to extract important information. Signal acquisition using non invasive technique with its processing has been a challenging labor preferred as it does not require any medical qualification. Measured Surface Electromyogram potentials are of the order of 0.5 mV with needle electrode and up to 10 µV for surface electrode. It contains frequency spectrum in range of 2 to 10 kHz with maximum signal power between 20 – 300 Hz for surface with 1000 samples/sec or more as sampling rate [6-8]. Some of the unique applications of Surface Electromyogram are prosthetic arm control, robot-human relation with voluntary and non-voluntary reflex excitations [9].

The effect of force contraction at different levels on median frequency of Surface Electromyogram has been reported in various studies. Researchers have shown that under isometric conditions there exists linear relationship between median frequencies of Surface Electromyogram and force contraction [10]. The formal scheme of this paper is organized in following manner: the basic theory behind Surface Electromyogram signal production from muscles and its acquisition using LABVIEW, subsequent signal conditioning and processing, then the feature extractions and finally results and conclusion.

2. SEMG SIGNAL ACQUISITION

SEMG signals were collected using non invasive electrodes at skin surface from the above elbow arm which have further been used for upper limb prosthetic control. A good acquisition of the EMG signal is a prerequisite for good signal processing. The placement of electrodes of proper location is an important issue as Surface Electromyogram signal amplitude is influenced by electrode location. Two positions, namely Biceps Brachii and Triceps Brachii were identified for signal acquisition in this experiment.

The raw signal extracted using non invasive electrode consists of various kind of noise, so signal conditioning and processing is required in order to reduce artifacts and getting important information for data analysis. Signal processing is implemented using LABVIEW as this platform provides many mathematical tools for analyzing signal charters-tics. Signal is amplified and passed from band-pass filter with high CMRR and gain in order to reduce motion artifacts (HPF) and noise (LPF) [11-12].

3. METHODOLOGY

Activities Performed: Subjects were seated on a chair. Each subject was asked to perform four different

ISSN: 2278 – 1323

movements for different muscles activation. These four different movements are as follows:

- *P1- Arm was in rest with downward position parallel to body.*
- *P2- Hand was moved upside. This position is called flexion elbow.*
- *P3- Arm was rotated in clockwise direction.*
- *P4- Arm was rotated in anticlockwise direction.*

Experiment: Five healthy male volunteers, age 22-28 year, weight 55-90 kg's and height of 170 to 180 cm participated in the complete part of this study. They were not informed of what the experiment was about. The Surface Electromyogram signal was acquired from two upper-arm muscles, the biceps and triceps brachii through non invasive electrodes placed on the midline of muscle belly using NI DAQ card and LABVIEW based soft scope code.

The samples were saved with specific name in the workspace. LABVIEW has large number of functions for numerical analysis and design and visualization of data. It is a graphical development environment with built in functionality for data acquisition, instrument control, measurement analysis, and data presentation.

About 1024 samples were recorded for the time window of 3000 ms of the soft scope in the workspace. A program was made to filter the signal in the frequency band 70 to 280 Hz in order to minimize movement artifacts and aliasing effect. The different parameters were then calculated. The general schematic of proposed system is illustrated in Figure 1. In order to understand sEMG signal's behavior, the experiment was carried out in two phases. In first phase, the arm is at "rest" without moving hand (No sEMG) and in second phase, it is with different movements (with sEMG).

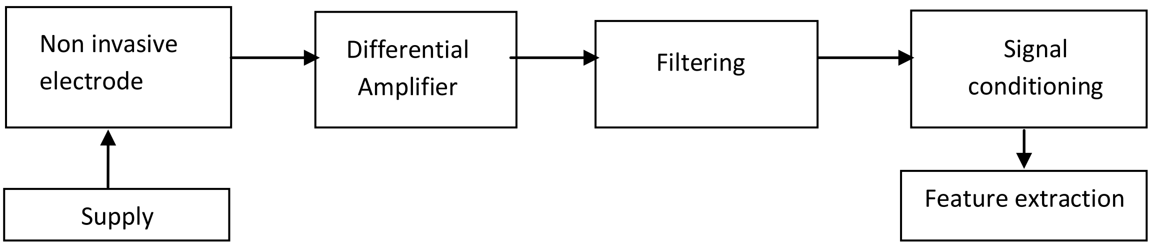

Fig. 1 Block diagram of the system

4. RESULT

As the surface electromyogram signal is a time and force dependent signal whose amplitude varies at random above and below the zero values, so signals analysis becomes important in a way to define characteristic properties of signal before its interpretation.

The processing of signal includes the following steps:

a. Filtering the signal with a band-pass filter (10 Hz and 500 Hz) updating the waveform graph cursors to represent the current values of the upper and lower cut-off frequency.
b. Dual channel spectral measurement on the prefiltered and the filtered signal to determine the frequency response of the filter.
c. Determination of different features like root mean square, standard deviation, energy of signal, integrated EMG and spectrogram. Front panel of the system is as presented in Figure 2.

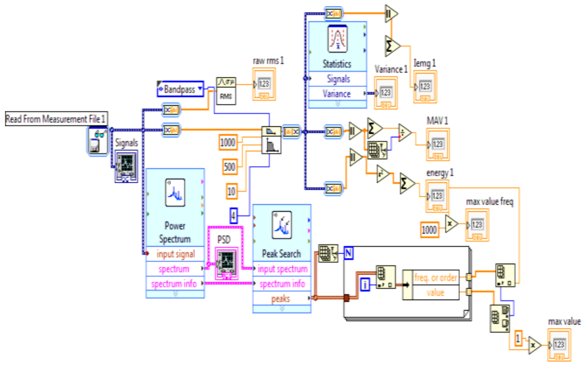

Fig. 2 Labview based code for feature extraction

The observations were taken from different subjects from two different points with different movements and are tabulated in Figure 3 & 4. It is clear that there values of RMS amplitude are more than in rest position from both muscles. From Figure 3, it is evident that there is change in V_{rms} value for flexion elbow movement for both biceps and Triceps muscles as compared to rest position. Figure 4 shows that Vrms for clock wise movements is higher than anti-clock wise movements with Biceps muscle and for Triceps muscle anti clock has higher value compare to clk movement.

ISSN: 2278 – 1323

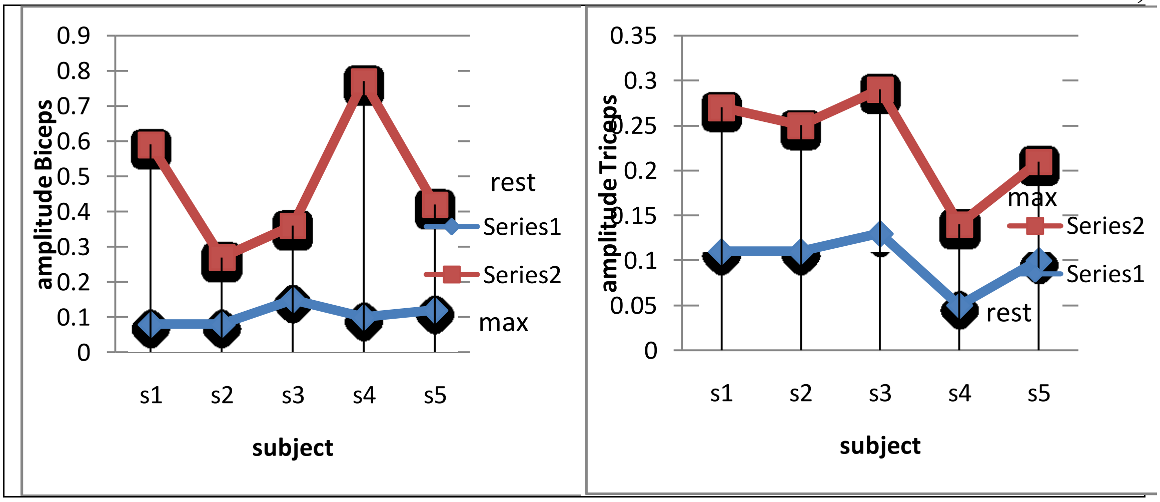

Fig.3 Results for position P1 and P2 for both muscles

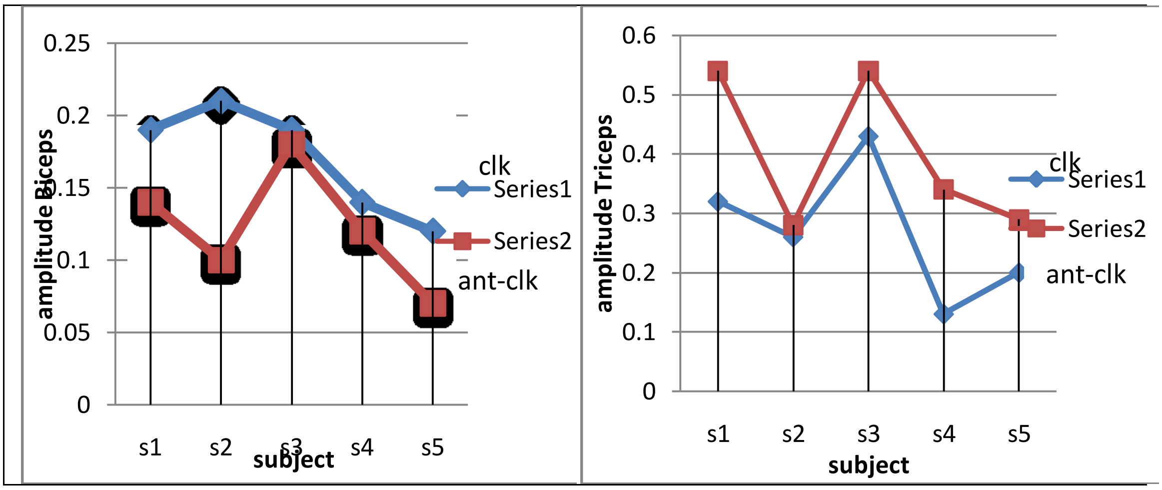

Figure 4 Results for position P3 and P4 for both muscles

Table 1. Comparison of Parameters

Parameters	No "SEMG"	With "SEMG"
V_{rms}	0.08	0.59
SD	0.062	0.588
Median Freq.	130	242
Energy	110	1036

5. DATA STATISTICAL METHOD

Here we are interested in refining the experiment to increase its sensitivity for detecting differences in the dependent variables. An effective step to achieve better performance for the classification of signal recorded at different voluntary contractions is the extraction of feature from the raw data before performing the multiple activities. The analysis of extracted features further helps to identify the significance of the surface electromyogram based muscular - force relationship existing in between them for the voluntary contractions.

In order to compare the means of the four independent variable groups (G1 – G4) and to decide about the effectiveness of the SEMG signal for different motions, a one way analysis of variance (ANOVA) has been utilized. The ANOVA Table with four groups for Biceps and Triceps motions is as shown in Table 2 and 3.

Table 2. ANOVA result for Biceps

ISSN: 2278 – 1323

Source of variation	sum of squares	(dof)	Mean square	Fisher ratio (F)	Significance value (p value)	critical value(fc)
(SSB)	0.638	3	0.212	35.11	0.0001	3.23
(SSW)	0.096	16	0.006			
(SST)	0.734	19				

Table 3. ANOVA result for Triceps

Source of variation	sum of squares	(dof)	Mean square	Fisher ratio (F)	Significance (p value)	critical value (fc)
SSB	0.186	3	0.062	5.22	0.0001	3.23
SSW	0.190	16	0.011			
SST	0.377	19				

The basic procedure is to derive two different estimates of variance from data, then calculate a statistic from the ratio of these two estimates. One of these estimates (SSB) is a measure of the effect of the independent variable combined with error variance. The other estimate (SSW) is of error variance by itself. The f-ratio is the ratio of between- groups variance to within groups variance. A significant F-ratio indicates that the population means are probably not all equal.

The F-ratio can be thought of as a measure of how different the means are relative to the variability within each sample. The larger this value, the greater the likelihood that the differences between the means are due to real effects. The F-ratio is the statistic used to test the hypothesis that the effects are real: in other words, that the means are significantly different from one another. Since F is SSB/SSW, a large value of F indicates relatively more difference between groups than within groups. Next V^2, which gives the percent variance due to between group variations, can be calculated as V^2 = SSB/SST.

There is a significant difference in amplitude gain across different motions, $F(3, 16) = 35.11$, $p < 0.05$ and $F(3, 16) = 5.223$, $p < 0.05$ for two independent muscles. From both Tables, since F ratio is greater than critical value (fc), means are significantly different and it is concluded that there is significant difference between the groups (SSB) than within groups (SSW). The p-values for biceps F (3, 16) and triceps F (3, 16) is 0.0001 which is < 0.05 so the null hypotheses of equal means is rejected and finally, it is concluded that the test statistic is significant at this level. Thus ANOVA found statistical differences between electrode positions ($p < 0.05$), surface electrode conditions, and the interaction between all groups.

6. CONCLUSION

Surface electromyogram signal is random in nature and some-how the complete study of these signals is complex. The work done on these signals at different locations with different movements will act as helping tool for future work to control artificial arm for above elbow. It can be concluded that biceps muscle is dominant for P-2 (clockwise) movements where as triceps muscle is dominant for P-4 (anti clockwise) movements, whereas for P-3 movement both has moderate values. Table 1 depicts different calculated features with "NO" surface electromyogram and "WITH" surface electromyogram giving relationship between muscular activity and force of contraction accordingly. The result also shows that content of the signal are highly dependent upon the proper location of placement of electrodes and in this way repeated factorial analysis of variance statistical techniques plays an vital role in identifying the effectiveness of recorded signal against different voluntary muscular contractions.

REFERENCES

1. Reaz MBI, Hussain MS and Mohd-Yasin F, "Techniques of EMG Signal Analysis: detection processing, classification and applications," *IEEE*

ISSN: 2278 – 1323

Transactions on Biomedical Engineering, vol. 10, pp. 11-35, 2006.

2. http://www.ncbi.nlm.nih.gov/pmc/articles/PMC1455479.
3. Mulla Mohamed R, "A Review of non-invasive techniques to detect and predict localized muscle fatigue", Sensors, vol. 11, pp. 3545-3594, 2011.
4. Basmajian JV and Deluca CJ, Muscle Alive, "Their function revealed by electromyography", Chapter 2, Ed. 5, Baltimore, Williams and Wilkins, pp. 21-63, 1985.
5. Jung Kyung, Kim Joo Woong," EMG Pattern Classification using Spectral Estimation and Neural network", SICE Annual Conference, Kagawa University, Japan, pp. 1108-1111, 2007.
6. Micera Silvestro, "Control of hand prostheses using peripheral information", IEEE reviews in BME, vol. 3, pp. 48-68, 2010.
7. Ryait HS, Arora AS and Agarwal R, "Study of issues in the development of surface EMG controlled human hand", Journal of Materials Science, Materials in Medicine, vol. 20, pp. 107-114, 2009.
8. Ahmadi A. Siti, Ishak J .Asnor and Ali Sawal, "classification of surface electromyographic signal using fuzzy logic for prosthesis control application", IEEE EMBS Conference on Biomedical Engineering & Sciences, pp. 471-474, 2010.
9. Ajiboye Bolu Abidemi and Weir F. ff. Richard, "A heuristic fuzzy logic approach to EMG pattern recognition for multifunctional prosthesis control", IEEE Transactions on Neural Systems and Rehabilitation Engineering, vol. 13, pp. 280-291, 2005.
10. K A Wheeler, H Shimada, D K Kumar and S P Arjunan, "A sEMG Model with Experimentally Based Simulation Parameters", 32nd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Argentina, 2010
11. Jung Kyung and Kim Joo Woong, "EMG Pattern Classification using Spectral Estimation and Neural network", SICE Annual Conference, Kagawa University, Japan , pp. 1108-1111, 2007
12. Zecca M and Micera S, "Control of Multifunctional Prosthetic Hands by Processing the Electromyographic Signal", Critical Reviews™ in Biomedical Engineering, 30, pp. 59–485, 2002

First Author, Tanu Sharma is working as Assistant Professor in Global college of Engineering, Khanpur Kuhi in Computer and Science Department since 2009. She is pursuing her M.Tech thesis in signal processing from BBSBEC Fathegarh Sahib. Her area of interest is signal processing and its modeling

Second Author, Mr. Karan Veer has completed his M.Tech in 2008 from Kurukshetra Univesrity. He has more than three years of research and teaching experience. Currently he is pursuing PhD from Thapar University, Patiala.

Third Author, Ravinder Agarwal is currently Professor in Electrical and Instrumentation Engineering Department at Thapar University, Patiala. He did his Ph.D. from National Physical laboratory, New Delhi in 1991. He has published 50 research papers in reviewed international journals of repute and more than 130 research publications in national and international conferences to his credit

ISSN: 2278 – 1323