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Research Article

Experimental Determination of SEMG Signal Characteristics and Elbow Movements

Retheep Raj[†*] and K S Sivanandan[†]

[†]Electrical Engineering Department, National Institute of Technology Calicut, Kozhikode, India

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Abstract

Work is intended to find out the relationship of biological signals with respect to the voluntary movement of human organs. Here the concentration is on elbow as a preliminary case, on experimental observation it is found out that the characteristics such as amplitude, frequency etc. of raw SEMG signals are very complex to relate it with the dynamics of elbow. A close analysis of Surface Electromyography (SEMG) signals through the well-established signal processing technique revealed some prospective encouraging result. So even though the relationship between the raw SEMG and the elbow kinematics is difficult to establish, the SEMG signal parameters like Integrated EMG (IEMG), Zero crossing (ZC), Root mean square value (RMS), Mean absolute value (MAV), Slope sign change (SSC) and Waveform length (WL) of the biological signal showed some useful relationship with the elbow dynamics. This experimentally verified relationship between the time domain parameters and the dynamics of human elbow is the content of the paper. The detailed description of this relationship is presented in the paper.

Keywords: *Surface Electromyography, time domain features of SEMG, Integrated EMG (IEMG), Zero crossing (ZC), Root mean square value (RMS), Mean absolute value (MAV), Slope sign change (SSC), Waveform length (WL), cross correlation.*

1. Introduction

The experimental technique deals with the development, recording and analysis of myoelectric signals are referred as Electromyography (EMG). Skeletal muscle contraction and relaxation happens when the nerve impulse from the central nervous system stimulates the muscle fiber by generating an action potential across the cell membrane of individual motor units. A muscle consists of a group of such motor units. The combined effect of such electrical potential developed by several motor units during the contraction and relaxation of muscles are medically referred as Electromyography (EMG) signal.

In the relaxed state of muscle, a noise-free EMG baseline voltage is observed in EMG graph. The factors effecting raw EMG baseline noise are, the quality of the EMG amplifier, the environmental noise and the condition of subject under investigation. For a better amplifier with properly prepared skin, the averaged baseline noise should not be higher than 3 to 5 microvolts. The investigation of the EMG baseline quality is a very important checkpoint of every EMG measurement. Interfering noise or problems within the detection apparatus may results in increased base activity or muscle.

The healthy relaxed muscle shows no significant EMG activity due to lack of depolarization and action potentials. The raw EMG spikes are usually random in shape, which means one raw recording burst cannot be precisely reproduced in exact shape. EMG signals can be measured using two methods, one is by piercing needle electrode into the muscles for measuring the EMG signal and other is a non-invasive technique, by placing the surface electrode over the skin surface above the muscle of interest. The EMG signals measured using the later method is commonly referred as surface EMG (SEMG) signal. SEMG signals contains details regarding the kinematics of muscles. For over the past few decades of years SEMG signals are commonly used for the diagnosis of neuromuscular disorders (Au & Kirsch, 2000) and control of prosthetic limbs (Asghari Oskoei & Hu, 2007).

Here in this paper the effect of different time domain parameters derived from the SEMG signal, obtained from the biceps brachii muscle of human hand with kinematics of forearm are observed and the best feature is detected from the sets of feature using cross correlation method. The rest of the paper is organised as follows, section 2 explains the details of data acquisition and prepossessing of SEMG signals, and different time domain features, section 3 details the experimental results and the conclusion of the work is given in section 4.

*Corresponding author: **Retheep Raj**

2. Experimental setup and feature extraction

2.1 Signal Acquisition and signal processing

SEMG signal are acquired from the biceps brachii muscle while performing continuous elbow extension and flexion with different velocities using a Bio amplifier. A standard bio signal acquiring circuit is implemented for the acquisition of SEMG signals using an instrumentation amplifier (INA 128P) and a high speed operational amplifier (OPA2132P). The gain value of the custom bio amplifier is designed as 10. The common mode rejection ratio of the circuit is 100 dB (minimum) and the bandwidth value is 200 KHz. A National Instruments My DAQ data acquisition card, is used for the acquisition of the amplified SEMG signal. The maximum sampling rate of the My DAQ data acquisition card is 200KSamples/sec and ADC resolution is 16 bit. Here in this experiment the SEMG data is sampled at a frequency equal to 10 K samples/sec and the all the prepossessing work is done by program coded using LABVIEW software. For the removal of DC base line shift and high frequency noise a third order IIR band pass filter is developed using program coded with LabVIEW. The lower and upper cut off frequency of the developed band pass filter is kept as 20 Hz and 400 Hz. Actual angle of elbow movement and actual angular velocity of elbow are obtained using a small powered triple axis accelerometer (ADXL 335) with analog output. The program to convert the acceleration to elbow bend angle and angular velocity of elbow are coded using LabVIEW program. The voltage value corresponding to acceleration of elbow is also read by the data acquisition card at a sampling rate 10 K samples/sec. The accelerometer module is fastened to the forearm of the subject. The data obtained from the analog accelerometer based tilt sensor are compared using a protractor chart hung on the wall. The picture of the experimental setup is shown in Fig 1.

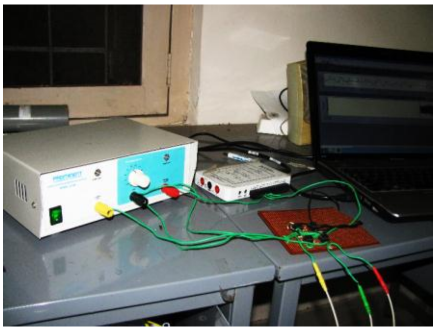

Fig. 1 Figure showing the experimental setup, NI MyDAQ data acquisition card, power supply and custom built bio-amplifier

2.2 Experimental Protocol

Four subjects are permitted to take part in the experiments. The average age of the participants is 28 years, average height is 1.68 m and an average weight is 69 Kg. Before the conduct of experiments, a prior permission is taken from each subject and also care is taken that none of the subjects are having any neuromuscular problems. The subjects are instructed to stay in standing position and the aceelerometer module is connected tightly to the forearm of the dominant hand of the subject. The SEMG acquisition is made using three disc type surface electrode made of silver-silver chloride (Ag-AgCl) material. One of the electrode (positive electrode) is placed at the center of the biceps brachii muscle of dominent hand and the second electrode (negative electrode) is placed at the lower end of bisceps brachii muscle. Both the measuring electrodes are placed at distance of 3 cm apart (Retheep Raj & Sivanandan K. S, 2015). Third electrode, the reference electrode is placed at upper side human palm. The subjects are said to take full rest before the conduct of experiment. The experiments are conducted by taking SEMG signal from the bisceps brachii while allowing the subjects to perform continuous full elbow extension and full flexion for few number of times with different angular velocity of movement.Fig 2 shows the placement electrode during the conduct of experiments.

2.3 Data Segmentation and Feature Extraction

The raw SEMG signal obtained from the surface electrode is stochastic in nature, but at the same time it is observed that certain parameters are repeatable with the kinematics of muscles (Ahmad, Ishak, & Ali, 2010). Before extracting the features from SEMG signal, the signal has to be segmented into small windows. Two different types of windowing methods are commonly used for extracting the SEMG parameters.One method is disjoint window method (Tenore et al., 2009) and the other method is overlapping window method (Huang, Englehart, Member, Hudgins, & Chan, 2005). Here in this work a disjoint window method is used for segmentation of SEMG signal. The window length is taken as 250 millisec. Seven time domain parameters, Integrated EMG (IEMG), Zero crossing (ZC), Root mean square value (RMS), Mean absolute value (MAV), Slope sign change (SSC), Wilson amplitude (WAMP) and Waveform length (WL) are extracted from each 250 millisec windows.

The mathematical integral of absolute value of SEMG signal amplitude gives IEMG. IEMG gives a good measure of muscle kinematics. The equation for extracting IEMG is given by

$$\mathrm{IEMG} = \sum_{k=1}^{N} |x_k| \tag{1}$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Zero crossing (ZC) is the measure of number times the SEMG signal amplitude crosses zero line. It is a measure of frequency information of SEMG signal. The equation for ZC is given as

$$\text{ZC} = \sum_{k=1}^{N} sign(-x_k * x_{k+1}) and \mid x_k * x_{k+1} \mid \geq 0 \quad (2)$$

$$sign(x) = \begin{cases} 1, x > 0 \\ -1, x < 0 \end{cases} \quad (3)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

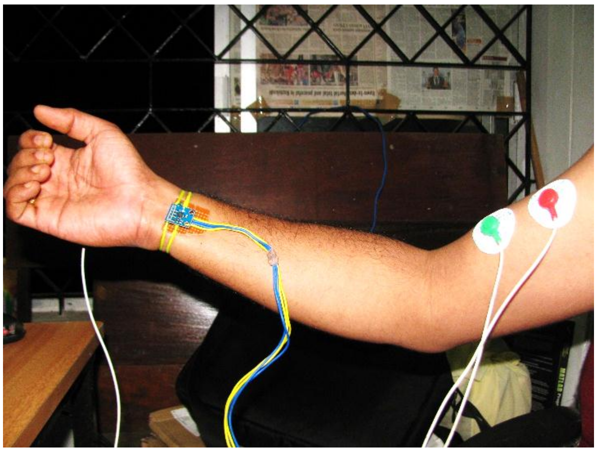

Fig.2 Figure showing the placement of Electrodes and accelerometer during the conduct of experiment.

Another feature which is commonly used in SEMG evaluation is Root mean square (RMS) value. The mathematical equation for finding RMS value is given by

$$RMS = \sqrt{\frac{1}{N}\sum_{k=1}^{N} {x_k}^2} \quad (4)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Mean absolute value (MAV) is another commonly used feature. It is almost similar to IEMG feature. The equation for MAV value is given as

$$\text{MAV} = \frac{1}{N}\sum_{k=1}^{N} |x_k| \quad (5)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Slope sign change (SSC) is the measure of number of times the slope of the SEMG changes the sign. It is also a frequency measurement of SEMG signal. The value of SSC can be represented mathematically by the equation

$$\text{SSC} = \sum_{k=1}^{N} (x_k - x_{k-1}) * (x_k - x_{k+1}) \geq 0 \quad (6)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Wilson amplitude (WAMP) is a measure of number of times the difference between successive points in SEMG signal is greater than a threshold value. Here in this work this threshold value is taken as $5\text{x}10^{-5}$. This parameter also gives the frequency information of the SEMG signal. The value of WAMP is given as

$$\text{WAMP} = \sum_{k=1}^{N} f(|x_k - x_{k+1}|) \quad (7)$$

$$f(x) = \begin{cases} 1, x > threshold \\ 0, \ otherwise \end{cases} \quad (8)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Waveform length (WL) parameter value indicates the complexity of the measured SEMG signal. This parameter is calculated using the equation

$$\text{WL} = \sum_{k=1}^{N} (|x_{k+1} - x_k|) \quad (9)$$

Where N is the number of samples of SEMG signals in one window and x_k is the SEMG signal.

Here the SEMG data is segmented into 250 millisec window using disjoint window method and seven time domian features are derived from each window of SEMG data.

3. Results

Here experiment is conducted with the aim of finding the relationship between few SEMG features and the kinematics of elbow movement. The subjects are asked to perform a repetitive flexion and extension of forearm, by keeping their non-dominant hand in full extension position. SEMG signals are taken from the biceps brachii muscles of the subjects. The obtained SEMG signals are segmented into 250 millisec non overlapping windows and different parameters are extracted from each windows. Graph showing the position of elbow angle during repetitive flexion and extension of forearm is presented in Fig 3. The relation between elbow angle and parameters like IEMG, RMS, SSC, WAMP, WL and ZC during ten repeated flexion and extension movement is shown in Fig4 to Fig 9. The graphs indicates that all the above said parameters are having the information regarding the position of elbow. To find the best parameters, a cross correlation is done between each of the above said parameters with the elbow angle data and the correlation coefficient value is calculated. The value of correlation coefficient for different SEMG features during repetitive flexion and extension of elbow is listed in Table1. The table clearly says that the parameters like IEMG, SSC and WL are having good correlation with the angular position of elbow when compared with the other parameters. IEMG and WL relates with the elbow angle in positive direction and SSC has an inverse relation with the elbow angular position. For detail analysis, the graph between angle and IEMG for one upward movement is selected and divided into two sectors and are shown separately in fig 10 and fig11. Sector 1 graph showing the relation between angle and IEMG when angle varies from 10^0 to 130^0 and sector 2 graph showing the relationship between angle and IEMG when angle varies 130^0 to 160^0. The relationship between average velocity of elbow movement and rate of change in IEMG for upward hand movement is shown in fig 12.

Table 1: Correlation coefficient values for different SEMG features and elbow angle during repetitive flexion and extension of elbow.

Feature Name	Correlation Coefficient value
Root mean square	+0.6093
Zero crossing	-0.6185
Slope sign change	-0.7248
Waveform length	+0.7252
Wilson amplitude	+0.5343
Moving average value	+0.7186
Integrated EMG	+0.7282

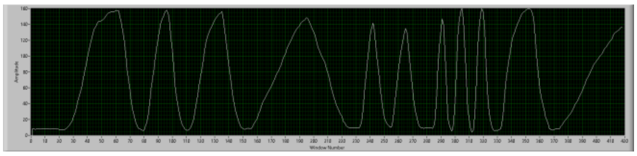

Fig 3: Graph showing the actual elbow angle during the flexion and extension of forearm.

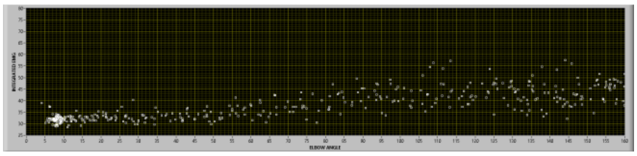

Fig 4: Graph showing the relation between IEMG and elbow angle during the flexion and extension of forearm.

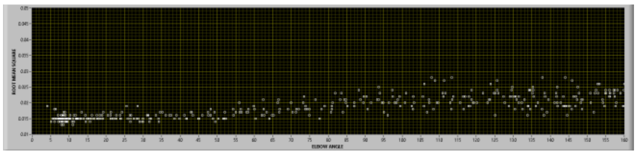

Fig 5: Graph showing the relation between RMS and elbow angle during the flexion and extension of forearm.

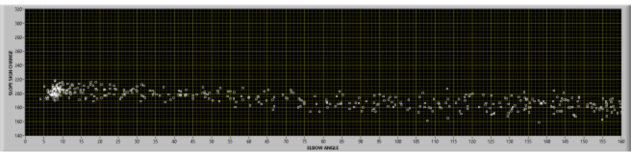

Fig 6: Graph showing the relation between SSC and elbow angle during the flexion and extension of forearm.

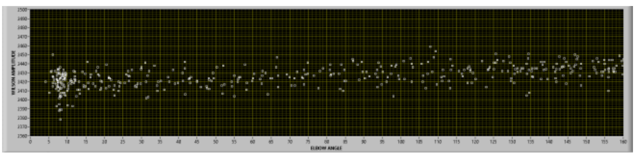

Fig 7: Graph showing the relation between WAMP and elbow angle during the flexion and extension of forearm.

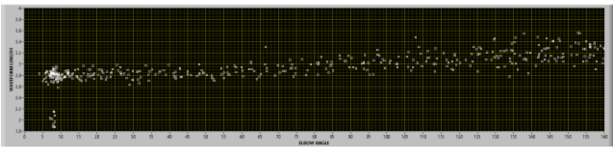

Fig 8: Graph showing the relation between WL and elbow angle during the flexion and extension of forearm.

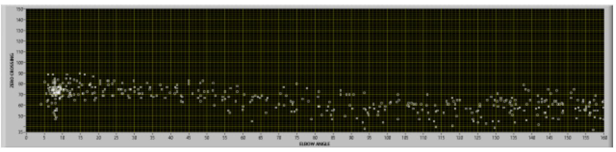

Fig 9: Graph showing the relation between ZC and elbow angle during the flexion and extension of forearm.

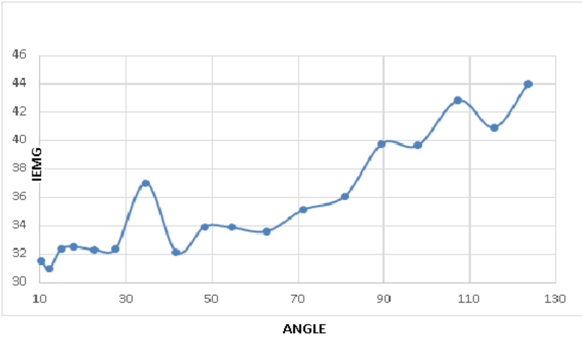

Fig 10: Graph showing the relation between angle and IEMG when angle varies from 10^0 to 130^0

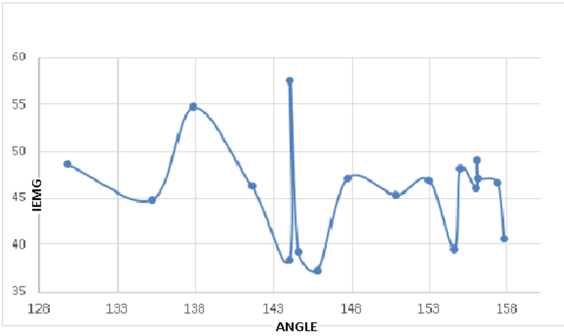

Fig 11: Graph showing the relation between angle and IEMG when angle varies from 130^0 to 160^0

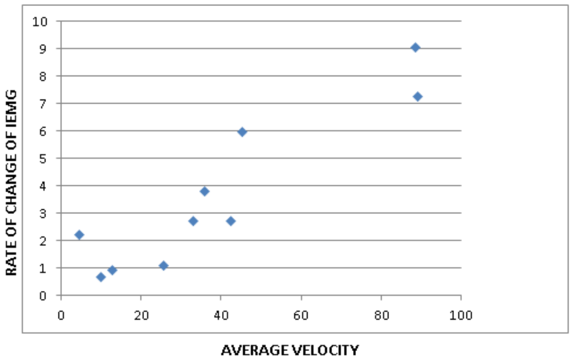

Fig 12: Graph showing the relation between average velocity of elbow movement and rate of change of IEMG for upward movement.

Conclusions

The experiments conducted on the subjects concludes that all the extracted features, Integrated EMG (IEMG), Zero crossing (ZC), Root mean square value (RMS), Mean absolute value (MAV), Slope sign change (SSC) and Waveform length (WL) of SEMG signals are showing some relationship with the elbow movement angle. Also the table showing the correlation coefficient of each parameter when cross correlated with elbow angle concludes that all the extracted parameters excluding Zero crossing and slope sign change shows a positive relationship with the elbow angle change. Zero crossing and slope sign change decreases with increase in elbow angle. Also it is clear from the table that IEMG, SSC and WL are considered as the best parameter for the estimation of elbow angle, since the correlation coefficient value of those parameters are high when compared with the other derived parameters. The work also establish that there exists a relationship between the average velocity of elbow movement and the rate of change of IEMG.

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