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Control of Stepper Motor Using Surface EMG Signals

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ABSTRACT: Surface EMG (Electromyography) signals are biomedical signals produced by the movement of muscles. EMG signals exhibit specific patterns for different activities and hence correct recognition of these patterns can be used for the control of assistive devices. The work includes developing a system that is capable of classifying EMG signals for different speeds and direction (flexion and extension) of a human elbow. The classified output is used to control a stepper motor which can be further used as a drive for assistive device. Data acquisition is done by placing surface electrodes on the brachii muscles of human arm. A reference electrode is also placed at the bony area. The signals are acquired using a modular body sensor kit BITalino. Signals are then processed in LabVIEW and features are extracted for pattern classification. Classification is done using Fuzzy Logic and the output is used to control the movement of a stepper motor. An accelerometer is also placed in the subjects arm for measuring the angular velocity of movements.

KEYWORDS: Data acquisition, Feature extraction, Fuzzy logic classifier, Signal processing, Stepper motor, surface EMG.

I. INTRODUCTION

EMG (Electromyography) are signals that are generated by skeletal muscles during movement. Surface EMG is obtained using surface electrodes. Related works on EMG signal can be found in literature. Classification of EMG signals based on PSO-SVM [1]. Use of discriminant analysis and Support Vector Machine for classification [2]. Use of Artificial Neural Networks and Radial Basis Function for pattern recognition [3]. Analysis depicting the superiority of ANFIS model (Adaptive Neuro-Fuzzy Inference System) in classification [4]. Evaluating time and frequency domain features to examine good feature vectors [5]. Optimum classification among two classes using a mother wavelet matrix [6]. People who are disabled, aged, or those with neuromuscular disorders always depend on an assistant to meet their daily activities. In order to avoid such circumstances and enable them to work as an individual, an assistive device can be used. These devices can be controlled by the surface EMG.

The aim of this work is to develop a system that is able to classify the patterns correctly and control a stepper motor so as to drive an assistive limb for supporting human elbow motion. The signal is classified for different speed and direction such as flexion and extension. The work includes acquisition of EMG signals from the biceps and triceps brachii muscle of human hand. Processing the signals to eliminate noise and other unwanted signals from the EMG. Feature extraction from the EMG which should serve as inputs to the classifier. Designing and developing a fuzzy logic for classifying EMG signals. Control of a stepper motor using the classified output.

The paper is divided into several sections. In the first section related works and a brief introduction was presented. Section two presents the methodology. Section three explains the data acquisition and signal processing. Section four explains the feature extraction in different domains. Section five explains the fuzzy logic classifier. Section six explains the stepper motor control. Section seven concludes the work.

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II. METHODOLOGY

The basic steps includes data acquisition, signal processing, feature extraction, classification and motor control.

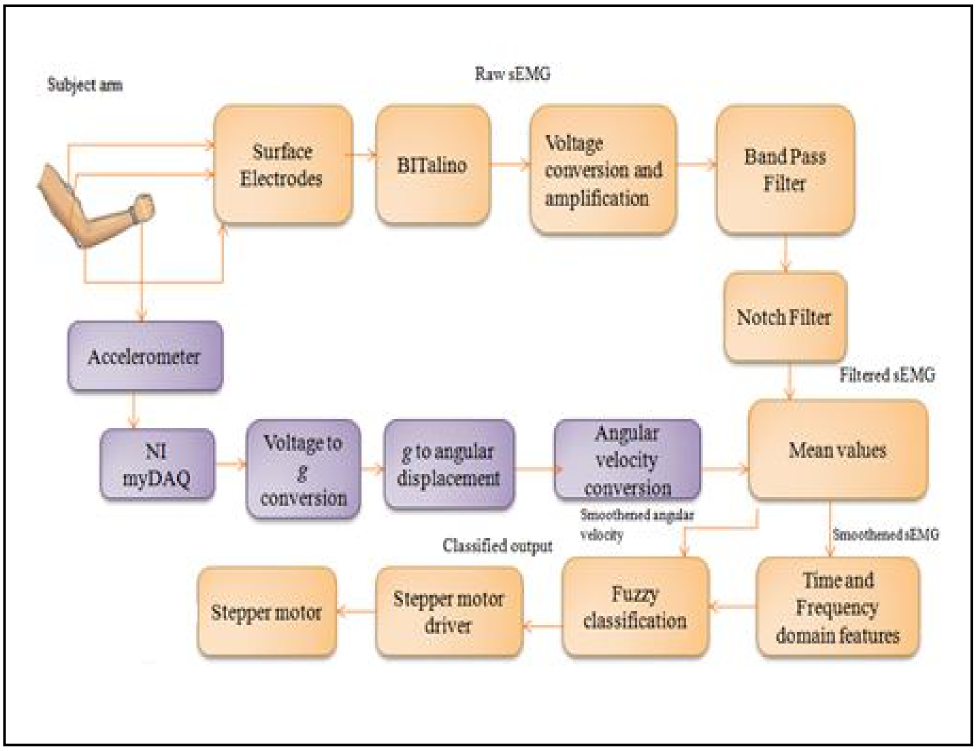

Fig 1. Generalized block diagram

Fig 1 shows the block diagram of the overall procedure. Surface electrodes are placed on the subjects brachii muscles of upper arm. The signals are then acquired using BITalino modular body sensor kit. Raw sEMG signals obtained are processed in LabVIEW for eliminating noise components. Mean values of these signals are taken for further analysis. In order to reduce its dimensionality features in time and frequency domain are extracted. These are given as inputs to the fuzzy logic classifier. An accelerometer is also placed in the subjects arm for measuring angular velocity of movement. Acceleration values are obtained from NI myDAQ, a data acquisition device. Further conversions are done in LabVIEW. The classified output from fuzzy logic is used to control the movement of a stepper motor.

III. DATA ACQUISITION AND SIGNAL PROCESSING

Three healthy subjects of the age group 22-25 are considered. Two Ag-AgCl pregelled surface electrodes are used. They are placed on the bicep and tricep brachii muscles respectively and a reference electrode is placed at the elbow region. They are then asked to perform flexion and extension of elbow at two different speeds. Each movement is performed five times. The signals are acquired using BITalino module. The sampling frequency used for the work is 1KHz. The data is then converted to voltage signals and then amplified.

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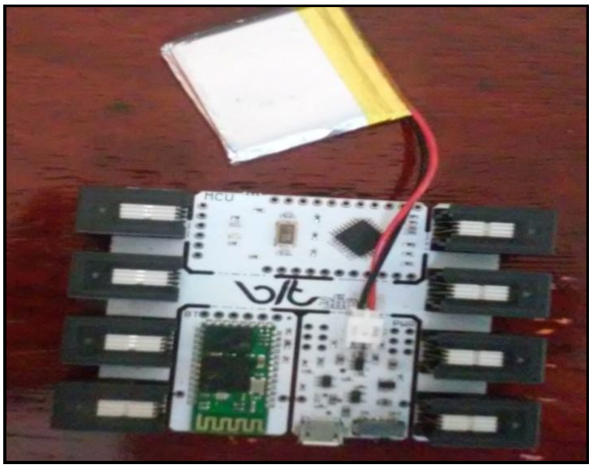

Fig 2. BITalino module

Fig 2 shows the BITalino module used in the work for acquiring EMG signals. It consists of a lithium polymer battery of 3.7V, a power board, micro controller unit, bluetooth module.

A three axis accelerometer ADXL335 is also placed in the subjects arm. The accelerometer can measure a full scale range of ±3g. Two parameters axis offset and sensitivity are calibrated before measurement [7]. The accelerometer values are acquired using NI myDAQ. The data from DAQ Assistant is plotted in waveform graph in the front panel of LabVIEW.

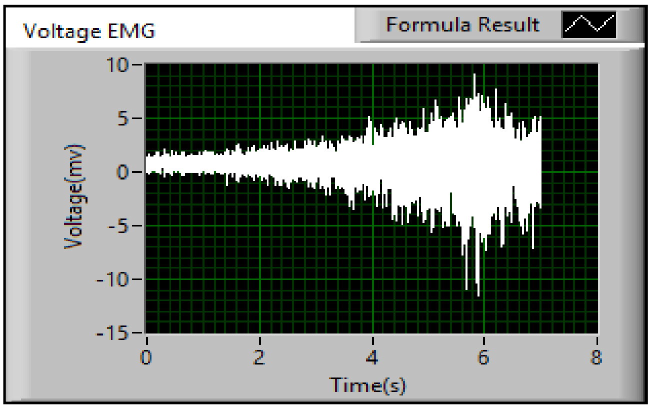

Fig 3. Raw EMG signal for slow flexion

Fig 3 shows a raw EMG signal obtained for slow flexion in the front panel of LabVIEW. The subject performs flexion of elbow for six seconds.

The EMG signals obtained from BITalino are raw signals and therefore need to be processed. The signals are converted to voltage values by Eq.1

$$\text{EMG value (Voltage)} = \frac{\left(\frac{x_i}{1023} - 0.5\right)3.3}{1000} \qquad (1)$$

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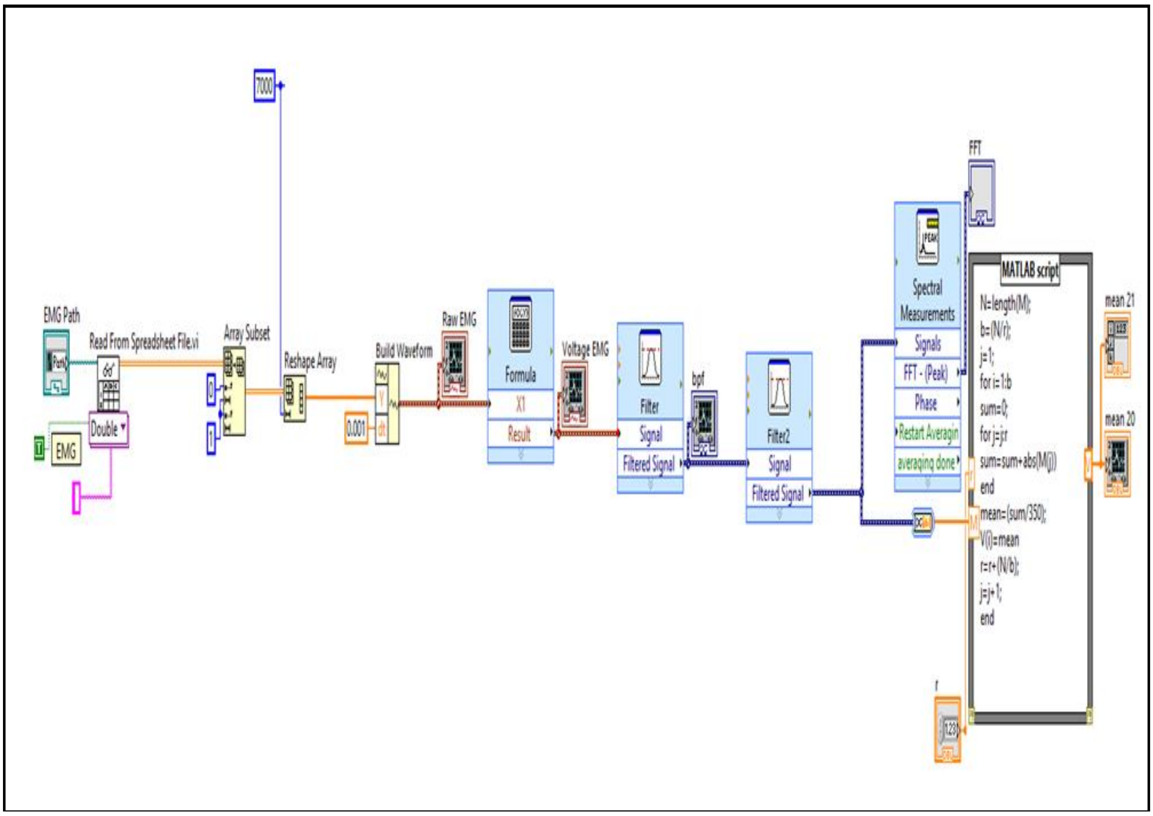

Fig 4. Signal processing in LabVIEW

Fig 4 shows the block diagram in LabVIEW for processing EMG signal. A fourth order butterworth bandpass filter of cut off frequency 50-150 Hz is used. A notch filter of frequency 50 Hz is also used to eliminate the power frequency interference [8]. The frequency spectrum of the signal is analyzed. The signal is rectified and divided into 20 segments of 350 ms duration for reducing the dimension. The mean value of each segment is then used for further analysis.

The data recorded by NI myDAQ is in voltage and is converted to g-force by Eq. 2.

$$Acceleration(g) = \frac{V_{in} - V_{offset}}{Sensitivity} \quad (2)$$

The values for axis offset and sensitivity obtained by calibrating are V_{offset}= 1.66V and Sensitivity = 0.33V/g. Angular displacement is calculated with respect to gravity axis. The angular velocity is then obtained and the mean values of segmented signals are plotted.

IV. FEATURE EXTRACTION

Features are extracted in time and frequency domain [9]. IEMG, MYOP, MAV are used in time domain features and wavelet coefficients are used in frequency domain.

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Integrated EMG (IEMG): IEMG is the summation of the absolute values of the sEMG signal amplitude. It is given by Eq. 3.

$$IEMG = \sum_{n=1}^{N} |x_n| \tag{3}$$

Myo pulse percentage rate (MYOP): It is an average value of myopulse output. It is defined as one when absolute value of the EMG signal exceeds a pre-defined threshold value. It is given by Eq. 4.

$$MYOP = \frac{1}{N} \sum_{i=1}^{N} f(x_i) \tag{4}$$

$$\text{where} \quad f(x) = \begin{cases} 1, & \text{if } x \geq \text{threshold} \\ 0, & \text{otherwise} \end{cases}$$

Mean Absolute Value (MAV): It is obtained as the average of full wave rectified EMG. It is given by Eq. 5.

$$MAV = \frac{1}{N} \sum_{i=1}^{N} |x_i| \tag{5}$$

Continuous wavelet transform (CWT): CWT of a signal S(t) is defined as the integral of the product between S(t) and daughter wavelets which are the time scale variations of a mother wavelet function. Mother wavelet function involves daubechies 4 wavelet. Fourth level decomposition was done and continuous wavelet coefficients of approximation signal were calculated.

V. FUZZY LOGIC CLASSIFIER

Features obtained are provided as inputs to the fuzzy logic classifier [10]. MYOP, IEMG and MAV are used to classify the EMG signal as flexion and extension. Speed classification is done using wavelet coefficients of approximation signals.

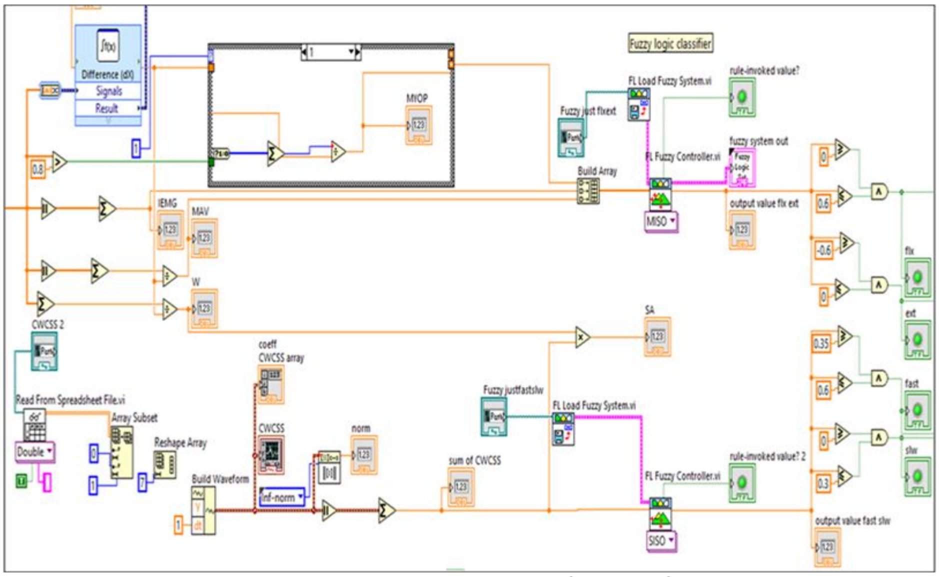

Fig 5. Block diagram in LabVIEW for classification.

Fig 5 shows the block diagram in LabVIEW for classification. Fuzzy IF-THEN rules are used to evaluate the class to which the inputs belong. Defuzzification is done based on center of area method. The classifier is able to classify the four different cases of elbow movement.

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VI. STEPPER MOTOR CONTROL

A. Hardware components

The components used includes a stepper motor, arduino board, motor shield, cable, power supply. Arduino UNO (R3) board powered by an USB cable. Motor shield consists of L293D IC. External power supply of 12V is supplied to the shield.

Fig 6. Stepper motor

Fig 6 shows the motor used for this work. It is a 12V/phase, 0.3A/phase, 800 steps/revolution, six wire hybrid stepper motor.

B. Experimental set up

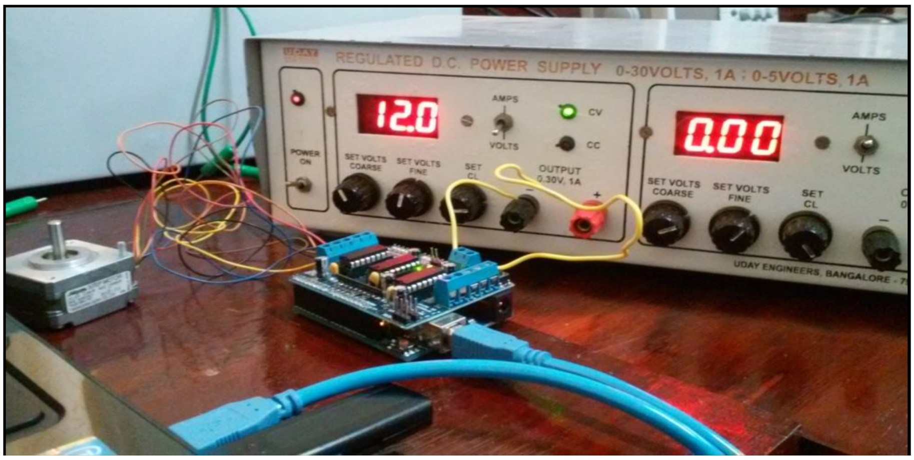

Fig 7. Stepper motor control circuit

Fig 7 shows the control circuit. The coils phases are first identified for the stepper motor. Stepper motor is connected to the motor shield in port 2 in bipolar configuration. Logic supply is obtained from arduino to which it is connected. A regulated dc supply set at 12 V is connected to the two terminal blocks on the shield. Arduino is powered by USB cable and a software is used to upload the code to the board. COM port and board type are set in Arduino IDE. The arduino is then interfaced to LabVIEW. Serial settings are entered in LabVIEW before running the program.

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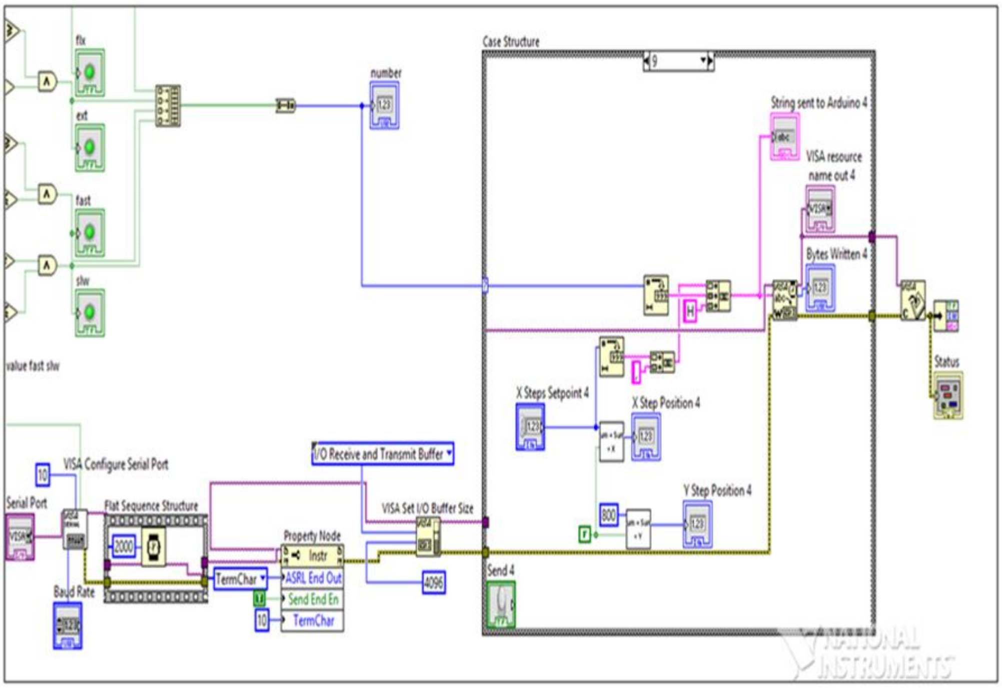

Fig 8. LabVIEW block diagram for stepper motor control

Fig 8 shows the LabVIEW block diagram for controlling stepper motor. Four different case structures are developed for fast flexion, slow flexion, fast extension, and slow extension. The output of fuzzy logic classifier is programmed in such a way that it gives correct movement of stepper motor for each of the classified output.

VII. RESULTS AND DISCUSSION

The motor rotates clockwise for flexion and anticlockwise for extension for both fast and slow speeds. A system that is able to classify EMG signals for different speed and direction of a human elbow was thus developed. Motor control that can be used in an assistive device for supporting human elbow motion was achieved. Data was acquired by surface electrodes placed on the subject. Corresponding angular velocity was also measured. Signals were processed and features were extracted to serve as inputs to the classifier. Correct classification of signals was given by the classifier. Stepper motor gave corresponding movements for the different classified outputs.

VIII. ACKNOWLEDGEMENT

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REFERENCES

[1] Abdulhamit Subasi, “Classification of EMG signals using PSO Optimized SVM for Diagnosis of Neuromuscular Disorders”, *Elsevier Journal of Computers in Biology and Medicine*, Vol. 43, No.5, pp. 576–586, 8 January 2013.
[2] Ahmet Alkan, Mucahid Gunay, “Identification of EMG signals using discriminant analysis and SVM classifier”, *Elsevier Journal of Expert Systems with Applications*, Vol. 39, Issue 1, pp. 44-47, January 2012.
[3] Juan Carlos Gonzalez-Ibarra, Carlos Soubervielle-Montalvo, Omar Vital-Ochoa, Hector Gerardo Perez-Gonzalez, “EMG Pattern Recognition System Based on Neural Networks”, *Eleventh Mexican International Conference on Artificial Intelligence: Advances in Artificial Intelligence and Applications*, 2012.
[4] Abdulhamit Subasi, “Classification of EMG signals using combined features and soft computing techniques”, *International Journal of Applied Soft Computing*, Vol. 12, Issue 8, pp. 2188-2198, August 2014.
[5] Angkoon Phinyomark, Pornchai Phukpattaranont, Chusak Limsakul, “Feature reduction and selection for EMG signal classification”, *Elsevier Journal of Expert Systems with Applications*, Vol. 39, Issue-8, pp. 7420–7431, 15 June 2012.

[6] J. Rafiee , M.A. Rafiee , F. Yavari , M.P. Schoen, “Feature extraction of forearm EMG signals for prosthetics”, *Elsevier Journal of Expert Systems with Applications*, Vol. 38, Issue 4, pp. 4058-4067, April 2011.

[7] Zohra Aziz Ali Manjiyani, Renju Thomas Jacob, Keerthan Kumar R, Babu Varghese, “Development of MEMS Based 3-Axis Accelerometer for Hand Movement Monitoring”, *International Journal of Scientific and Research Publications*, Vol. 4, Issue 2, pp. 1-4, February 2014.

[8] Jingpeng Wang, Liqiong Tang, John E Bronlund, “Surface EMG Signal Amplification and Filtering”, *International Journal of Computer Applications*, Vol. 82, No.1, pp.15-22,November 2013.

[9] Angkoon Phinyomark , Chusak Limsakul and Pornchai Phukpattaranont , “A Novel Feature Extraction for Robust EMG Pattern Recognition”, *Journal Of Computing*, Vol. 1, Issue 1, pp.71-80,December 2009.

[10] Timothy J Ross, “Fuzzy Logic with Engineering Applications”, Third Edition, ISBN: 978-81-265-3126-4, 2010.