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Research Article

Estimation of elbow joint angle from Time domain features of SEMG signals using Fuzzy Logic for prosthtic control

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Abstract

In this work an attempt is made to estimate the elbow joint angle from Surface Electromyography (SEMG) signal during dynamic contraction using Fuzzy logic technique. Here the SEMG signals are taken from the biceps brachii of subjects during flexion and extension of eblow. To estimate the elbow joint angle, the SEMG signals are segmented into 250ms by adjacent window technique and two time domain parameters like Integrated EMG (IEMG) and Zero crossing (ZC) are extracted from windowed Raw EMG signals. If-then rules of fuzzy logic are derived from the experimental findings. The estimated values of elbow joint angles are compared with the actual angle values. A two Dimensional robotic arm animations is also coded using LabVIEW and are incorporated to the output of fuzzy logic system to simulate the estimated angle. The system is validated using regression value. Regression value obtained from the experiment is 0.7975.

Keywords: *Surface Electromyography, Feature extraction, Fuzzy logic, Prosthetic control.*

1. Introduction

All types of human body voluntary movements can be achieved only by contraction and relaxation of skeletal muscles. All such activities begin by sending an electrical stimulus signal from central nervous system towards muscles indicating muscle contraction or relaxation. The reception of such signals leads to some electrical excitation in individual muscle fiber. A group of such muscle fibers leads to contraction or relaxation of muscles and thereby leads to mechanical movements. Electromyography signal is the algebraic sum of electrical excitation of a group of muscle fibers associated with the activation of muscles within the pickup area of electrodes. The EMG signals from human body can be measured in two different ways, one is non-invasive method, by using surface electrodes and other is invasive method using needle electrode. The discomfort and the difficulty of placing the electrodes in the same area of the muscles for every repeated measurements can be overcome to an extend by using non-invasive method of measurement. SEMG type measurement technique has effected with artifacts and noises but because of it easiness and safety in measurement, this technique is more popular among researchers.

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2. Methods

2.1 Instrumentation and Data collection

SEMG signals from subjects are acquired using a custom build Bio amplifier circuit designed using INA128P, instrumentation amplifier and OPA2132P, high speed operational amplifier. The schematic diagram of the bio-amplifier circuit is shown in Fig. 1. Gain of the amplifier circuit is set as 10. The amplified SEMG signals are then acquired using National Instruments data acquisition device (MY DAQ) at a sampling rate of 10K samples/sec and with an ADC resolution of 16 bit.

Surface EMG signals are taken from four healthy male subjects with an average age of 30 years, average height of 1.68m, and an average weight of 64Kg. Myoelectric signals are detected by placing three electrodes. Two of them are kept as measurement electrode and third act as reference electrode. The measurement electrodes are placed at the biceps branchii muscles, one at the center and other at the lower end of the biceps branchii. The subjects are allowed to take complete rest before undergoing experimentation, this is to take care that the muscles are not strained during experimentation. Ag-AgCl surface electrodes are used for sensing the EMG signal. The distance between the electrodes is kept as 3Cm (G. Venugopal *et al*, 2014).

The subjects are allowed to stay in standing position and said to relax all muscles. The subjects are asked to perform elbow flexion and extension tasks. The rotation ranged from full extension (with elbow angle of 0^0 or the forearm is kept vertical or the forearm is in anatomical position) to full flexion (elbow angle equal to 140^0). Elbow Angle is measured by an analog tilt sensor.

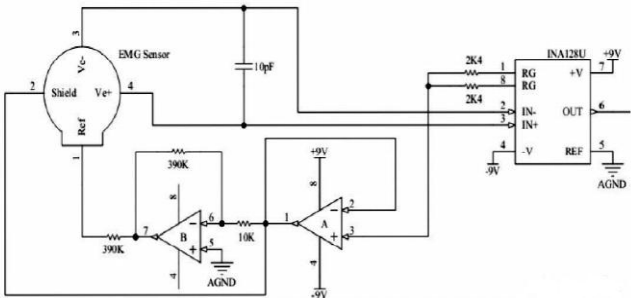

Fig.1 Schematic diagram of Bio amplifier circuit

2.2 Feature Extraction

Raw EMG signal is segmented into 250 millisecond window[T. Lorrain *et al*, 2010], with 0% overlap and two time domain parameters Zero crossing (T. Lorrain *et al*, 2012) and Integrated EMG (IEMG)(Z. Yang *et al*, 2014;T. Lorrain *et al*, 2012) are calculated from each segment.

For a given time series signal zero Crossing is the measure of number of times the amplitude values crosses the zero y-axis. It provides the approximate estimation of frequency domain properties. The equation for Zero Crossing (ZC) of EMG is given by the formula

$$\mathrm{ZC} = \sum_{k=1}^{N} \mathrm{sign}(x_k * x_{k+1}) \text{and} \mid x_k * x_{k+1} \mid \geq \text{threshold} \qquad (1)$$

Integrated EMG (IEMG), is the mathematical integral of the absolute value of the raw EMG signal. It is also defined as the area under the curve of the rectified EMG signal. IEMG is calculated by equation

$$\mathrm{IEMG} = \sum_{k=1}^{N} |x_k| \qquad (2)$$

These time domain features are used as the inputs to the fuzzy logic system.

2.3 Estimation of Elbow joint angle

Several attempts had been made for estimating the human motion intensions from surface EMG signals. Jingdong zhao *et al*..(J. Zhao *et al*, 2005) Proposed a method to classify the motion pattern using parametric autoregressive model using Levenberg Marquardt (LM) algorithm. Autoregressive moving average with exogenous output(ARMAX) model (P. K. Artemiadis *et al*, 2006) has also been used to extract the human elbow joint angle. Giho Jang *et al*. [G. Jang *et al*, 2014] proposed another method based on spring damper pendulum model for estimating shoulder angle during flexion movement. Another estimating method was developed using a multi input multi output (MIMO) black box model by Panagiotis k Artemiadis *et al*.(P. K. Artemiadis *et al*, 2009) In this work they estimated the shoulder and elbow angle and the force exerted by the subject. H J Yu *et al*.(H. J. Yu *et al*, 2011) proposed another method to calculate the elbow joint angle. Here in this work a third order polynomial function model is used for the estimation.

Here in this work a fuzzy logic system is used for estimating the human elbow joint angle. The two time domain parameters, Integrated EMG and Zero crossing (ZC) obtained from raw SEMG signals are fed as the input to the fuzzy logic system and the estimated angle is taken as the output of system. Fig. 2 shows the block level diagram of fuzzy logic system.

Triangular shapes are used as the membership function for both inputs and output. Center of area method is used for defuzzification. Feature extraction and angle estimation using fuzzy logic are done using LabVIEW 2013 software with the help of control and fuzzy tool kit. As the EMG obtained from the subjects vary with person to person and also vary with the conditions of measurement and placements of electrode. This problem can be overcome by normalizing the time domain parameters (Y. M. Aung *et al*, 2013). The obtained time domain parameters are normalized to a value between 0 to 10. The equation for normalization is given by the formula

$$Y_{\mathrm{Norm}} = \frac{(Y_{\mathrm{MaxNorm}} - Y_{\mathrm{MinNorm}})(Y - Y_{\mathrm{Min}})}{(Y_{\mathrm{Max}} - Y_{\mathrm{Min}})} + Y_{\mathrm{Min}} \qquad (3)$$

Where Y_{MaxNorm} and Y_{MinNorm} are the maximum and minimum value of normalized output. Y_{Min} and Y_{Max} are the maximum and minimum value of parameter before normalization.

Four membership functions are designed for inputs and output and are named as very low, low, high and very high. Fig 3 shows the membership functions of ZC, IEMG (inputs) and Angle (output).

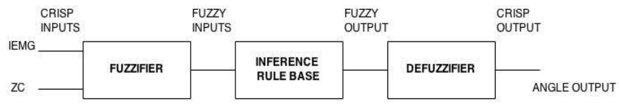

Fig.2 Block level diagram of fuzzy logic system

Sixteen if then rules are derived from the experimental findings for the estimation of elbow joint angles. Rules are shown in Table 1.

3. Results

The raw EMG signals show a base line shift and also contain low frequency signals due to motion artifacts. These are removed by a preprocessing stage, consists of a third order Butterworth Band Pass filter with lower and upper cutoff frequency 20Hz and 400Hz using LabVIEW. The preprocessed raw SEMG signals are shown in Fig 4.

Time domain parameters like ZC and IEMG are extracted from preprocessed raw SEMG signals for two cycles of rotation of elbow joint, ranging from full extension to full flexion. These parameters are then normalized to a value ranging from 0 to 10. Fig 5 shows the normalized parameters for different angle of elbow position. Elbow joint angle is measured using tilt sensor. The output of tilt sensor is shown in Fig 6.

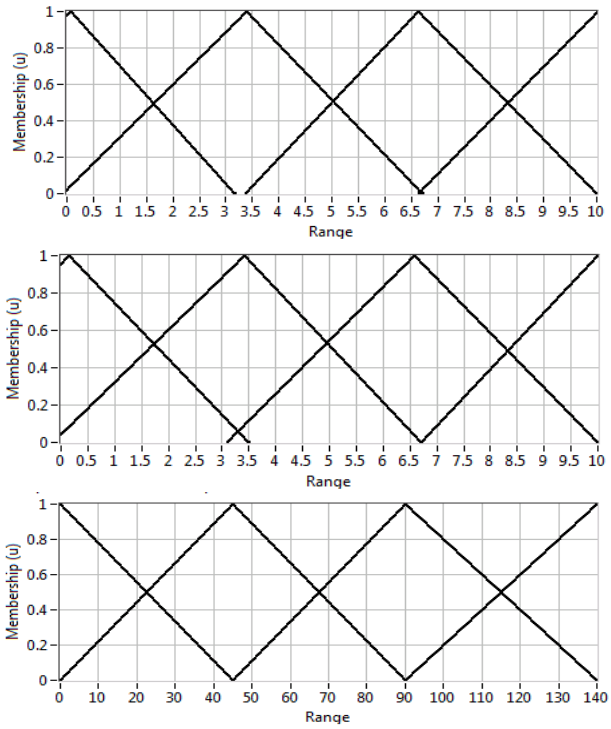

Fig.3 Membership function of (1)ZC (2)IEMG (3) Angle

Table 1 Rule base for fuzzy logic

Sl No.	ZC	IEMG	Angle
1	Very High	Very Low	Very Low
2	Very High	Low	Very Low
3	Very High	High	Low
4	Very High	Very High	High
5	High	Very Low	Very Low
6	High	Low	Low
7	High	High	High
8	High	Very High	High
9	Low	Very Low	High
10	Low	Low	Low
11	Low	High	High
12	Low	Very High	Very High
13	Very Low	Very Low	Low
14	Very Low	Low	High
15	Very Low	High	High
16	Very Low	Very High	Very High

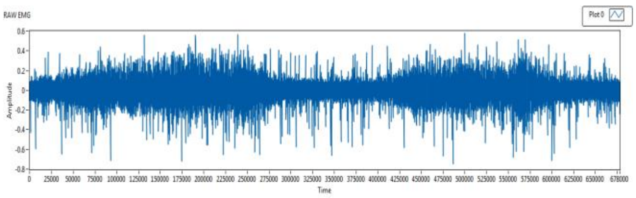

Fig.4 Preprocessed SEMG signal for two cycles of Elbow joint angle movement

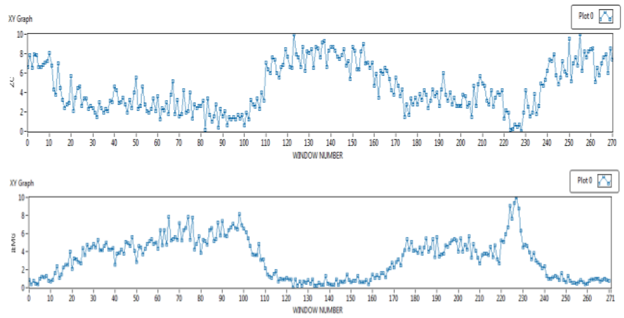

Fig.5 Change in time domain parameters (1) ZC (2) IEMG with elbow flexion and extension for every 250msec windows size for two cycles of Elbow joint angle movement.

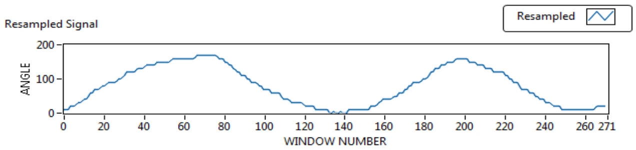

Fig.6 Tilt sensor output for every 250msec window size for two cycles of Elbow joint angle movement.

The obtained time domain parameter values are fed into the fuzzy logic system for the prediction of elbow joint angle. The inference rule base of fuzzy logic system predicts the elbow joint angle from the time domain parameters.

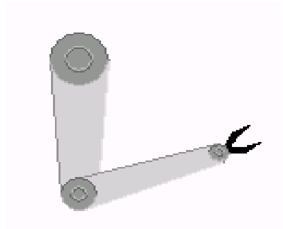

Fig.7 Result of robotic arm simulation coded using LabVIEW

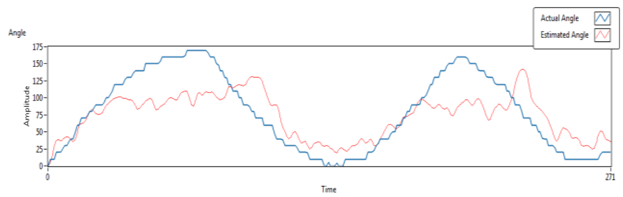

Fig.8 Result showing Actual angle and estimated angle

In the final stage the predicted elbow joint angle from the output of fuzzy logic system is given as the input to the two dimensional robotic arm animation coded using LabVIEW 2013 software with the help of robotic tool box. The obtained result of robotic arm simulation is shown in Fig 7. The estimated angle from the fuzzy logic system and the real angle obtained from tilt sensor are shown in Fig 8.

The designed fuzzy logic system is validated by finding the regression value, r. The regression plot is shown in Fig 9. The regression value obtained is 0.7975.

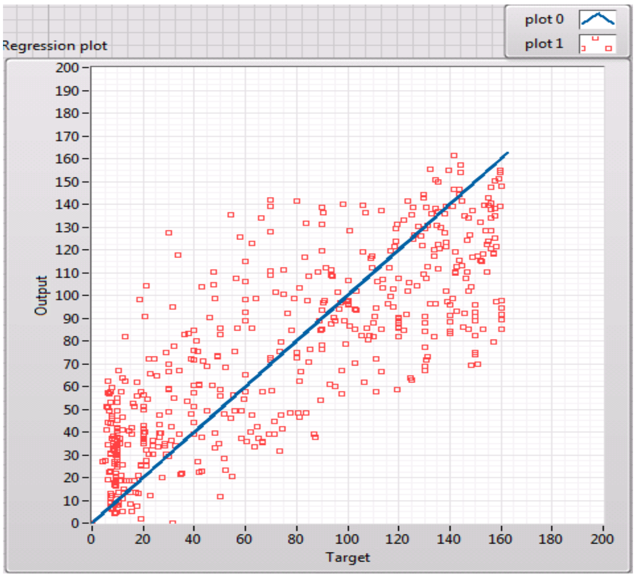

Fig.9 Regression graph showing the validation of fuzzy logic system

Conclusions

A Fuzzy logic system is developed for estimating elbow joint angle from time domain parameters obtained during contraction and relaxation of elbow muscles.

The result obtained from the experimentation indicates that the angle estimation can be done easily using time domain parameters and by using fuzzy logic technique. Compared with other estimation technique using artificial neural network, fuzzy logic technique requires no training, So that this can be implemented for real time estimation with very little effort. The obtained estimated angle is fed to a robotic arm simulation and imitated human elbow movement. The system is validated by finding the regression value. A regression value of 0.7975 is obtained from the experiment.

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