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Fuzzy Controlled Myoelectric Arm using Lab VIEW

[1]Mishel Ann Mathew,[2]Nimisha Mohan P,[3]NimithaThampy,[4]VidhyaRaveendranath,[5]K M Abubeker
[1][2][3][4]UG Scholar,[5]Assistant Professor
Department of Electronics and Communication
Amal Jyothi College of Engineering, Kottayam, Kerala, India

Abstract: **The technology of myoelectric arm is developing day by day to make it more beneficial for the patients .This paper describes the design of myoelectric-controlled partial-hand prosthesis to help physically disabled people, who had traffic or industrial accident and the lost function. The proposal focuses mainly on extract electromyogram (EMG) signals generatedduring contraction of the biceps. The detected EMG signals must first be processed, digitized, and converted to Pulse Width Modulation (PWM) signals, which are then used to control the designed prosthesis mechanism. The knowledge required to implement the proposed prosthesis design project thus covers signal-processing techniques, labview interface design, and a scheme for controlling a servomotor mechanism.**

Keywords— **Electromyogram(EMG), LABVIEW**

I. INTRODUCTION

Myoelectric systems have received widespread use as controls of prosthetic devices for individuals with amputations or congenitally deficient upper limbs. Myoelectric systems make use of EMG signals to implement the necessary motions. EMG signals are now emerging in the fields of diagnosis of neuro muscular diseases, controlling of many prosthetic devices etc. This paper focuses on EMG based control of prosthetic device. This includes acquisition of EMG signals using surface electrodes. The acquired signals are interfaced using LabVIEW which includes pre-processing of the acquired signals, feature extraction and generation of PWM signals. This PWM signals are then used to drive the prosthetic device. As EMG signals are complex in nature, the EMG signal classification is a prime concern. For this we use Fuzzy logic approach. Fuzzy logic has the capability to deal with uncertain and imperfect signals. The use of Labview has provided a convenient and efficient tool in the classification of EMG signals. We focus on EMG based control of prosthetic device to aid handicapped people to improve their quality of life. Since this paper outcomes a practical prosthesis, it open ups student interest to mechatronic education and its importance in the field of biomedical engineering.

II. SIGNAL ACQUISITION

Surface EMG signals are acquired from three positions of the arm using surface electrodes. The surface electrodes used is the disposable electrodes. Two electrodes are placed on the flexor carp umulnaris (below elbow) and biceps branchii (between elbow and shoulder) and a reference electrode is placed on the wrist position. Disposable electrodes require skin preparation for ignoring artifacts. Alcohol is used for skin cleaning and then electrodes are placed. The obtained signals are accessed using Data Acquisition System and the EMG signal values are stored in a spreadsheet in a computer.

III. LABVIEW INTERFACING

A. LabVIEW LabVIEW also known as Laboratory Virtual Instrument Engineering Workbench by National Instruments is a system that help us to do visual programming. In this paper we mainly focus on the biomedical toolkit of LabVIEW that help us to acquire medical signals and process it efficiently and produce the required output. It includes full-featured, multichannel data logger for streaming bio-signals to disk for playback and analysis. B. B. Pre-processing of EMG signals EMG signals are prone to external noise sources and has varying and contradictory amplitudes. The EMG signals are shifted above the baseline due to human interference. So these surface EMG signals are shifted to the zero line. A Butterworth band pass filter of lower cutoff frequency 10 HZ and higher cutoff frequency 500HZ is used for de-noising. It is a combination of low pass filter and high pass filter. A high pass filter is used to attenuate DC offset noise voltage and a low pass filter is used for removing environmental noise. The baseline shifting and filtering of EMG signals is shown below

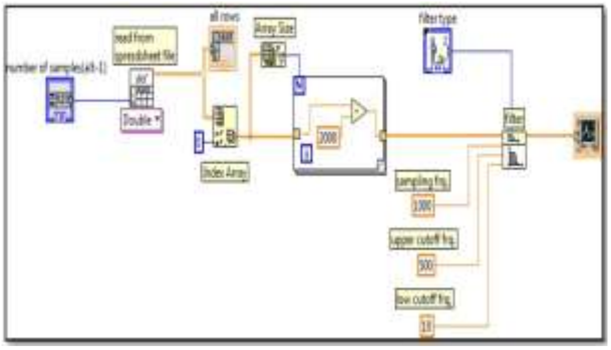

Fig 1.Block diagram of program for baseline shifting

C. Feature Extraction As EMG signals are complex and varying, selection of features is essential for signal classification. Multiple features are selected as it is difficult to obtain a particular feature for the intended motion. Three features are extracted for the efficient classification of signal. These are Mean Absolute Value(MAV), Integrated EMG(IEMG) and Zero Crossing Rate(ZCR) and their description is given below. Mean Absolute Value(MAV):It is the average rectified value and is calculated using the average of the absolute value of the EMG signal. It is an indication of muscle contraction levels. Integrated EMG(IEMG):It is the summation of the absolute values of the surface EMG signal amplitude and is an indication of muscle activity. Zero Crossing Rate(ZCR):It shows the number of times a signal crosses the axis of abscissas and is a useful feature for the detection of diseases. where D. Fuzzy Designer and EMG Signal Classification EMG signal classification is done based on fuzzy system logic. Here input output relationship is created based on test values (using large number of sample values). The extracted features of EMG signals namely Mean Absolute Value(MAV), Integrated EMG(IEMG), Zero Crossing Rate(ZCR) are chosen as input variables. The output tested here is of grasping and lifting(1Kg). Therefore output variables are defined as grasping(GRASP) and lifting(LIFT). Two different range sets are provided for the three features extracted based on subjects for grasping and lifting(1Kg) respectively. If it does not belong to the range it means continue testing(CT).

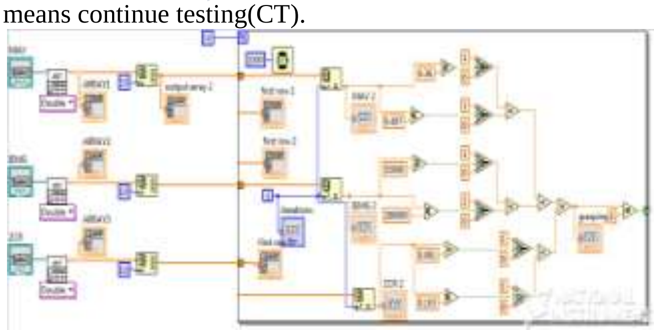

Fig 2. *Block diagram for classifying EMG signals for grasping*

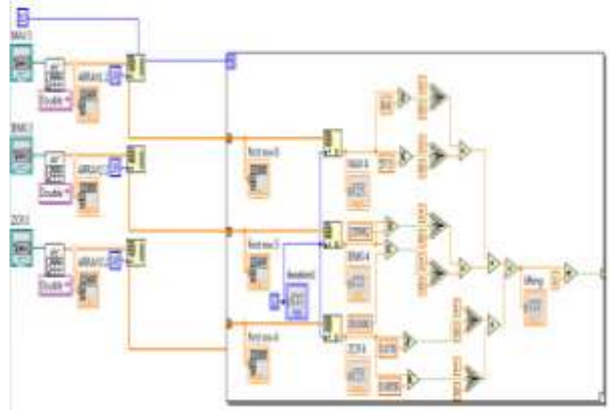

Fig 3. *Block diagram for classifying EMG signal for lifting.*

The classifier signal is compared. If it is equal to the grasping or lifting signal(1Kg), the output is given to a DAQ Assist from which we output the corresponding PWM signal.

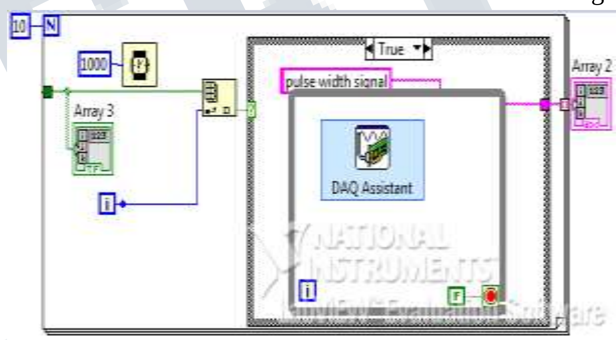

Fig 4. *Signal comparison and PWM output.*

Pulsewidth signals provided would be in the range of approximately 800 microseconds as high time(pulse width) and 1200 microseconds as low time.

IV. DATA ACQUISITION UNIT

Data acquisition is the process of sampling signals that measure real world physical conditions and converting the real samples into digital numerical values that can be manipulated by the computer and vice-versa. Here Data Acquisition Unit (NI USB-6211) is used to output the pulsewidth generated in labview to trigger the prosthetic arm. NI USB-6211 is a bus- powered USB M series multi- function DAQ module optimized for superior accuracy at fast sampling rates. It offers 16 analog inputs ,250kS/s single channel sampling rate, 2 analog outputs,

4 input digital lines, 4 digital output lines, 4 programmable input ranges(±0.2-±10V)per channel, digital triggering and 2 counter/timers. PF14 and PF15 ports are used to take the output for grasping and lifting(1Kg)

respectively. These are digital output ports and the common digital ground from data acquisition unit is provided to the servomotor common ground.

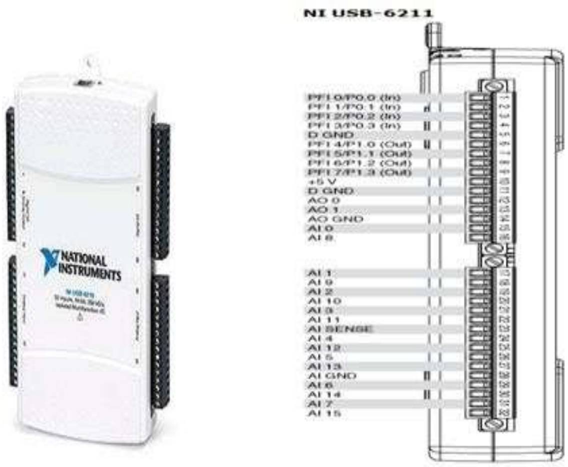

Fig 5. *Data Acquisition Unit* - NI USB-6211

V. ROBOTIC ARM

The PWM signals for each grasp and lift movement are taken via a Data Acquisition System through two ports. This PWM signal is given to a robotic arm which has six servomotors attached to it where five servomotors are attached to each finger and one servomotor to wrist. These servomotors operate by sending a timed +5V pulse to the onboard electronics which is repeated every 20ms. This pulse corresponds to a servo position usually from 0 to 180 degrees.

- 5V for 500 microseconds=0.5 milliseconds and corresponds to 0 degrees
- 5V for 1500 microseconds=1.5 milliseconds and corresponds to 90 degrees
- 5V for 2500 microseconds=2.5 milliseconds and corresponds to 180 degrees

Here V0006 Mega Robo Kit analog servomotor has been used. It provides three output pins(wires). Black wire from the servo motor is the ground pin which is connected to the ground and also to the data acquisition unit ground port. Red wire is where the +5V or high pulse provided. To the yellow or white wire the input signal from data acquisition unit is provided.

Fig 5. *Overview of the project.*

CONCLUSION

The classifier is designed to a given set of data. The classifier gives output which is compared and respective pulsewidth provided for subject's grasp and lift movements(1kg). The classifier is tested with available set of data. After comparing the classifier output, respective PWM signal is taken out for grasp and lift movements through DAQ Assist. Corresponding to the output pulse from the Data Acquisition System, the robotic arm performs the grasping or lifting action in accordance with the surface EMG signals acquired.

The surface EMG signals acquired which are varying and contradictory in nature are classified using fuzzy logic. An input output relationship is created. In this paper feature extraction and classification of EMG signal has been done for grasping and lifting(1Kg) action. The obtained movements are then used to drive a robotic arm to implement these actions. The success rate is 75.3% for grasping and 70.8% for lifting. The efficiency can be increased if more meaningful EMG values are given. Here the grasp and lift operations are given separate conditions. The future scope deals with these operations on a combined rule basis and also incorporating more actions to be implemented.

Table 1: Validation of classifier for grasp movement using without weight

Sample	Zero Crossing Rate	Integrated EMG	Mean Absolute Value	Classifier Movement
1	0.084	118427.114	7.228	CT
2	0.093	89950.528	5.49	GRASP
3	0.096	89842.341	5.484	GRASP
4	0.093	112880.048	6.89	GRASP
5	0.103	86227.88	5.263	GRASP
6	0.089	103713.524	6.33	CT
7	0.092	102655.948	6.266	GRASP
8	0.092	85246.662	5.203	GRASP
9	0.096	83789.012	5.114	GRASP
10	0.1	78597.794	4.797	GRASP
11	0.102	78008.567	4.761	GRASP
12	0.093	100753.118	6.149	GRASP
13	0.1	84584.24	5.163	GRASP
14	0.091	111600.219	6.812	CT
15	0.096	87633.375	5.35	GRASP

Table 1: provides the values of EMG features extracted and the corresponding movements obtained based on these values(grasping condition).

Table 2 : provides the values of EMG features extracted and corresponding movements obtained based on these values(lifting 1 Kg) condition.

Table 2: Validation for classifier for lift movement for 1Kg

Sample	Zero Crossing Rate	Integrated IEMG	Mean Absolute Value	Classifier Movement
1	0.075	212875.596	12.993	CT
2	0.08	180310.72	11.005	LIFT
3	0.073	315901.897	19.281	CT
4	0.081	160536.819	9.798	LIFT
5	0.08	211018.989	12.88	LIFT
6	0.079	210331.853	12.838	LIFT
7	0.08	187093.187	11.419	LIFT
8	0.079	162172.574	9.898	LIFT
9	0.082	144715.513	8.833	LIFT
10	0.074	233407.752	14.246	CT
11	0.08	173143.104	10.568	LIFT
12	0.073	253189.106	15.453	CT
13	0.08	252919.371	15.437	LIFT
14	0.079	327839.97	20.01	LIFT
15	0.082	177560.296	10.837	LIFT

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