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Surface Electromyographic signal based finger prosthesis control using ANN

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Abstract—**This paper represents the development of surface Electromyographic (sEMG) signal-based finger prosthesis control. A filter & amplifier circuit captures the EMG signal from the surface of the human hand that can be recorded using ATmega-2560 micro-controller. The analysis of the output signal is done to study time domain features. In this paper, standard deviation, mean, a variance is taken as time domain feature. The signal is then trained using simple Artificial Neural Network to classify accurately two finger motion i.e. grip motion and thumb-index finger motion.**

Keywords- ATmega-2560, sEMG Signal, Electrode, Servo, Instrumentation Amplifier, Moving Average, ANN

I. INTRODUCTION

Electromyography is used as a diagnostic tool for a neurological disorder. Presently it is also being used in rehabilitation of amputees in the form of the robotic prosthesis to recapture their ability to perform complicated physical movements of the lost human hands. The process of recording the electrical signal transmitted by the Motor Neuron to control the muscles is Electromyography (EMG). The movement of body parts is possible through muscle contraction and expansion and brain send excitation signal through the central nerve system. When a motor unit is activated motor MUAP is produced [1]. The activation from the central nerve system repeated continuously for generating force and it results in producing EMG.

Electromyography (EMG) is a suitable approach for human-machine interface in the prosthetic hand's control. However, these super prosthesis hands are highly complex and expensive. Though the EMG signal is complicated, this signal can be measured by applying a biopotential sensor like electrode [2]. Electrode acts as a transducer between the ionic transport of the nerve and the electron flow in copper wire. In general, at first the EMG signal is captured by electrode and amplified. After that the EMG signal is processed to remove noises or any other elements that may affect the data. In present condition the challenge consist of complex motion identification, high cost and unpredictable behavior in real world. In this research authors have proposed a simple method for motion detection which avoids complex design and complex hand gesture prosthetic hand. The prosed technique is targeted for low income people in 3rd world country as prosthetic hand is very costly and could be unaffordable for many people.

II. LITERATURE REVIEW

In this area, many researches have been made on developing an algorithm, improving recent methods, noise reduction and feature extraction. EMG recording is relatively new technology though the first documented experiment on EMG is done by Francesco Redi in 1666 [4]. In 1961 the first artificial hand was developed in Russia by A. E. Kobrinski, the Otto Bock Orthopaedic [3-5]. There are still limitations on detecting and feature extraction of EMG signal; it cannot provide enough information or data to develop more accurate and efficient EMG based devices [6, 7]. Several studies have attempted to extract features of the EMG signal and to classify signal patterns [6-8]. Extracted EMG signals were sent wirelessly to PC for analysis [9]. Recently researcher controlled prosthetic hand based on torque estimation using EMG signal. In this research, they worked on direct torque control method for the prosthetic hand. In order to estimate the joint torque from EMG signals, an artificial neural network by the feedback error learning schema is used by them [10]. The real-time virtual prosthetic hand is made for two movements [11]. The system proposed in [11] demonstrated 84% accuracy. However, Support Vector Machine (SVM) was superior than the other three classifiers on both accuracy and reached an accuracy of 80%. The proposed technique could be a potential technique to be used in prosthetic control[12]. In future, prosthetic hand probably can accept command direct from the human nerve system and perform multiple tasks with high accuracy. Currently The accuracy of the Prosthetic hand is a major concern. Moreover, Automatic hand movement recognition based on sEMG signals is a promising approach in prosthesis hand control application [13-15].

III. METHODOLOGY

A. System Architecture

EMG signal in electrode contains noise so it cannot be used for processing and it cannot be read by the normal microcontroller. In this case, at first, an instrumentation amplifier is used which has a high common mode rejection ratio. A high common mode rejection is necessary to reject all the noise captured by an electrode. CMRR should be over 80 dB. In preamplifier, stage gain is 22. After amplification, the signals are passed through 2nd order Sallen key high pass which cut-off frequency is 20 Hz and low pass filter of the cut-off frequency of 500 Hz. Then it goes through an amplifier with a gain of 101. Then, the signal is passed through another high pass filter of the cut-off frequency of 67 Hz to eliminate 50 Hz noise. ATmega-2560 reads data using the ADC module and then transferred to PC using the serial port. The EMG signals amplitude's range is between 0 to 10 millivolts (peak-to-peak) or 0 to 1.5 millivolts (RMS). Also, The frequency of an EMG signal is between 0 to 500 Hz. However, maximum energy of the EMG signal lies between 50-150 Hz [16]. EMG signal depends on skin resistance. So, skin preparation is important. The objective of the present work is to extract the EMG signal and analyse different time domain feature in real time. Received data is processed and features are extracted. Then the neural network algorithm classifies the data and gives output. The output of the neural network is matched and gives movement decision. The block diagram of the whole system is given in figure 1.

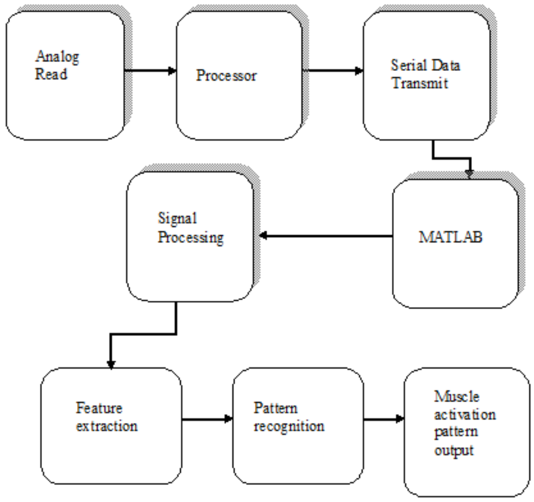

Figure 1. Functional block diagram of the proposed technique

B. EMG electrode and Its placement

The electrode provides a noninvasive way to detect and analyze to EMG signal. For proper skin preparation, the dead cell should be removed by alcohol so that skin resistance keeps between 5k to10K Ohms. The longitudinal axis of the electrode and Length of the muscle fiber should be parallel. A reference point is used as a ground for the EMG signal extraction and the electrode is placed in the elbow, as the elbow is electrically neutral and far from target muscle. This electrode in the elbow is directly connected to the instrumentation amplifiers reference pin which is shown in figure 2.

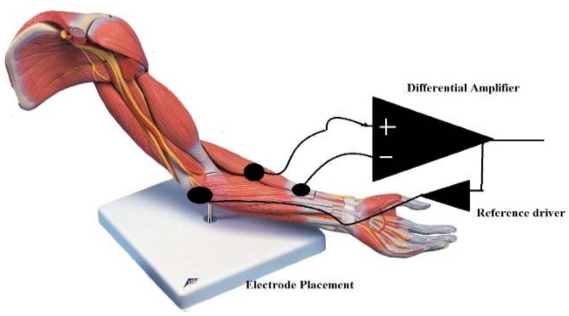

Figure 2. Placement of EMG electrodes to extract sEMG signal

C. Pre-amplification

A different amplifier with high CMRR ratio is used to eliminate dominant 50Hz noise. The common CMRR ratio of the instrumentation amplifier should be 90-120 DB. A RC low pass filter is used at the input for removing RF interference. Then the signal respectively passes through the 2nd order Sallen key High pass and low pass filter of the cut-off frequency of 20 Hz and 500 Hz respectively to remove the noise from the signal. To eliminate 50 Hz noise the signal passes through a high pass filter of cut-off frequency 67 Hz. The output of the Sallen key Filter is feed to a gain amplifier. The schematic diagram of the analog frontend used to record the sEMG signal is provided in figure 3. An inverting amplifier is used in this case.

Gain,

$$G = -\frac{R_F}{R_I} \tag{1}$$

R_F=100k, R_I=1k, So gain is 100 in this stage.

D. Data acquisition

The amplified EMG signal has a negative portion in its signal which cannot be read by the ADC module. So, 2.5V bias voltage is added at the output of the gain stage using an operational amplifier. The resolution of the analog to digital conversion (ADC) module which is integrated in ATMega 2560 is 10 bits. The sampling frequency was 1 kHz. Then the signal data fed to the main computer using UART serial communication protocol at a speed of 115200 bps.

E. Signal processing

sEMG signals are irregular in the pattern. Each time for the same pattern of muscle movement, the generation of the same pattern of muscle signal is impossible. And this signal rapidly fluctuates while a muscle contraction or extension occurs. So, for classifying muscle movement pattern from the sEMG signal, some signal processing steps must be adopted to smooth this signal. The classification accuracy mostly depends on a good signal processing method. Researchers usually use three types of signal processing method to process sEMG signal i.e. time domain, frequency and time-frequency domain signal processing [17]. Time domain signal processing approach has been used in this paper.

sEMG signal is a non-stationary signal. For real-time processing of a non-stationary type signal, moving average or, moving window filter are the popular techniques which have been implemented in this paper. A moving window of 80 data sample has been selected which shifts to right after each 10 data sample is received and averages the data points that are covered by the moving window. When the average value crosses a certain threshold, level is detected as the muscle motion has begun. And when this average value goes below the threshold is detected as the motion has been the end. The motion window within these start and end motion is then truncated and used for further processing. The data sample out of this motion window corresponds to no motion.The truncated signal is meaning for motion detection. Hence for each truncated window feature extraction procedure is applied. So, each truncated window will have value of Variance (VAR), Standard deviation (STD) and Mean Absolute Value (MAV).

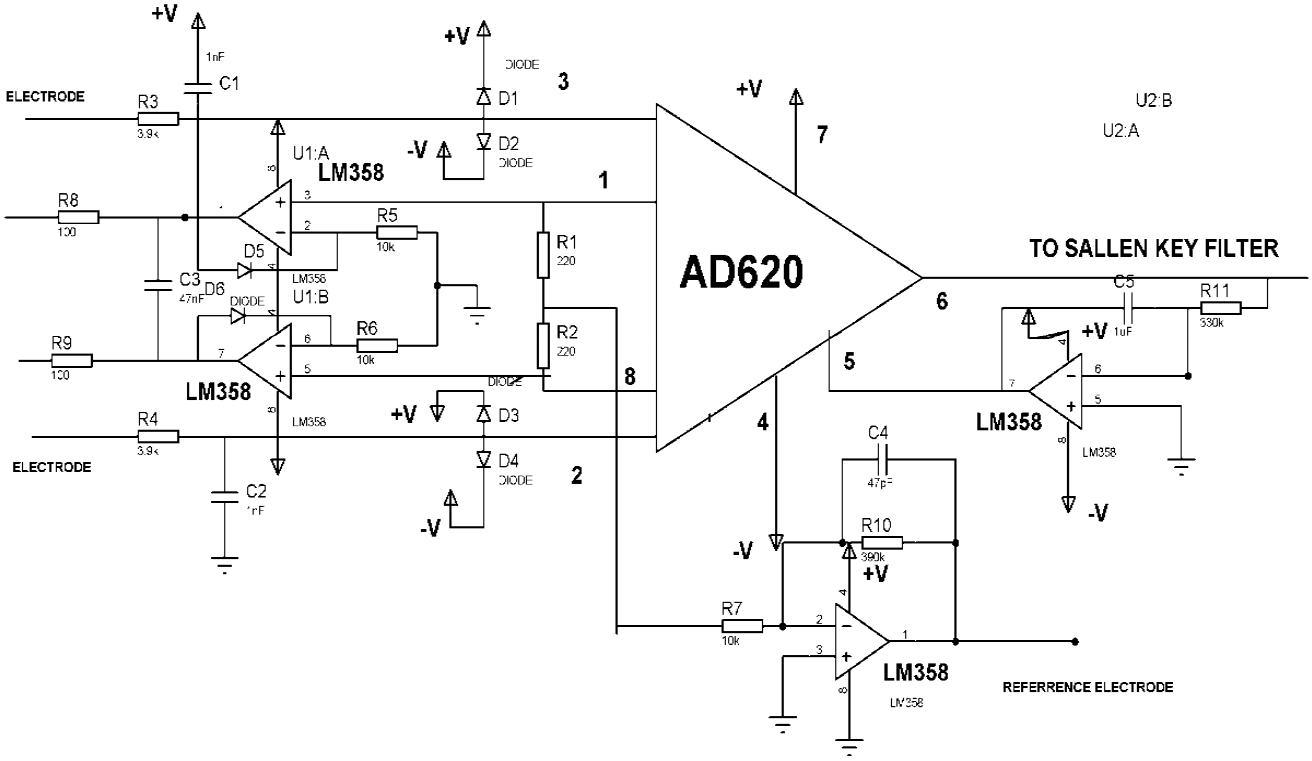

Figure 3. Circuit schematic of the analog frontend used to record the sEMG signal.

After the application of moving window/average filter the signal becomes smoother than the raw signal which is shown in Figure 4. The data sample within the motion window is used for feature extraction and classification.

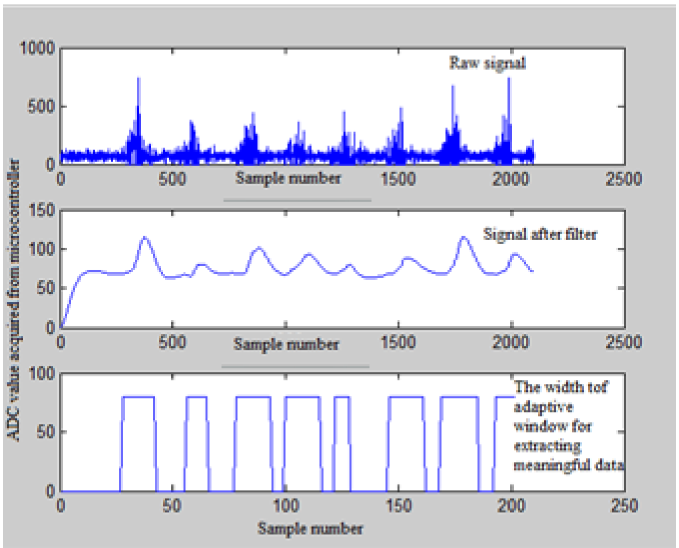

Figure 4. Raw EMG signal and signal after filtering which is used in ANN training

F. Feature extraction:

Feature extraction is the most important part for classifying a signal using an Artificial Neural Network.[18] A good feature creates more distance amongst the different patterns of the same signal. Features are like some characteristics that a signal has e.g. amplitude, RMS value, standard deviation etc. From the moving averaged signal three-time domain features has been calculated which are Variance (VAR), Standard deviation (STD) and Mean Absolute Value (MAV). The features were extracted for two types of finger motion i.e. grip motion and thumb-index finger motion. Other parameters do not change sharply for two types of finger motion, so these three features are the input for the artificial neural network architecture.

Variance determines how spreads out the data samples are from their mean. The mathematical definition of variance is the average of squared differences from the mean.

$$\sigma^2 = \frac{\sum(X-\mu)^2}{N} \tag{2}$$

Standard deviation is the square root of variance.

$$\sigma = \sqrt{\frac{\sum(X-\mu)^2}{N}} \tag{3}$$

Where σ is the standard deviation, N denotes the number of samples, X is the value of the sample and μ is the mean of the data samples.

These three features or characteristics of the sEMG signal for different motion has been shown in the figure 5below.

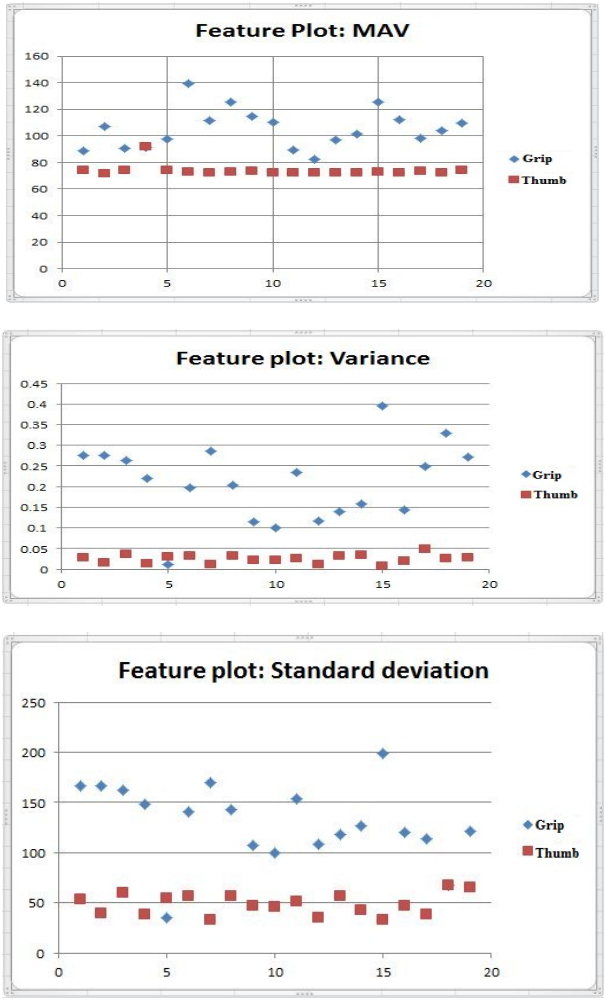

Figure 5. Scatter plot of the Features and class segmentation of one single sample (X and Y axis interpretation)

G. Classification

Artificial Neural Network (ANN) approach has been incorporated to train input-output data so that it can classify the muscle movement pattern more accurately. There are several algorithms for implementing Artificial Neural Network from which the Back-Propagation Algorithm has been adopted as the learning method.

ANN architecture basically executes a hypothesis function. This hypothesis function uses a transfer function which may be linear e.g. purely or, non-linear e.g. sigmoid function.

For software implementation of Backpropagation algorithm and neural network architecture, MATLAB software was used. MATLAB has a built-in NETWORK class that can be customized to evaluate the designed neural network architecture. ANN architecture consists of three-layer i.e. input layer, hidden layer, and output layer. Each layer includes some neurons or, units. The hidden layer can be more than one in number depending on the application. This architecture uses a feed forward network that takes the features as input vector, processes the data through the hidden layer and changes the weight matrices and shows the recognition logic on the output layer. Figure 6 shows the architecture of Artificial Neural Network

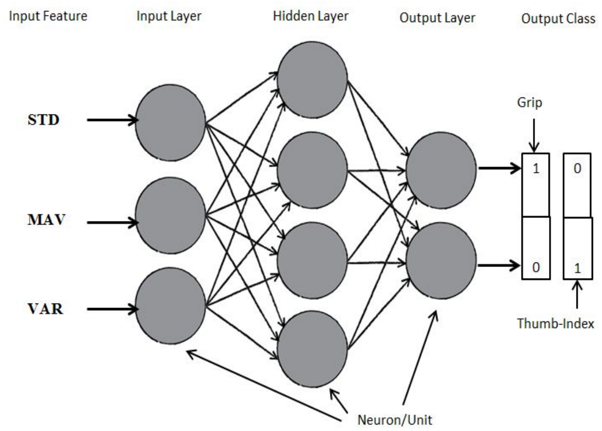

Figure 6. Artificial Neural Network Architecture

In this application, the number of the hidden layers is 20 and each hidden layer includes 10 neurons. The number of input feature is 3 and the number of output pattern is 2. The total number of training of sample for training the network is 192. The NETWORK class was customized to use a sigmoid function as the transfer function.

IV. RESULT

A prototype of this proposed method is constructed and shown in Figure 7. The proposed prototype has 2nd degree freedom. The approximate cost of the proposed prototype is around 75 dollar. Table I shows just one sample data for one grip motion and thumb index motion. MAV,STD,VAR are calculated for every Grip motion and Thumb-Index motion performed and listed. These sample data are used for training the ANN model. The output vector of the corresponding motion is shown in Table II. Table III shows the experimental result of 5 samples. In these 5 samples MAV, STD, VAR are input, and ANN will a vector out put . With this Vector output corresponding Grip/ Thumb-Index Motion is produced by servo motor.

TABLE I. SAMPLE TRAINING INPUT VECTOR

Feature Input	Finger Motion	
	Grip Motion x (5/1023)V	Thumb-Index Motion x (5/1023)V
MAV	118.71	78.28
STD	166.54	57.53
VAR	0.2757	0.0329

TABLE II. SAMPLE TRAINING OUTPUT VECTOR

	Grip motion	Thumb-index motion
Output Vector	1	0
	0	1

TABLE III. SAMPLE INPUT/OUTPUT DATA SET AND RECOGNITION RESULT

Input Features	TS1	TS2	TS3	TS4	TS5
MAV	105.51	71.99	73.81	123.93	72.63
STD	141.17	59.857	38.30	169.55	54.69
VAR	0.1983	0.03557	0.0144	0.2860	0.02968
Output Target	1	0	0	1	0
	0	1	1	0	1
Recognition Result					
	0.8873	0.1505	0.0387	0.9248	0.1331
	0.1127	0.8495	0.9613	0.0752	0.8669

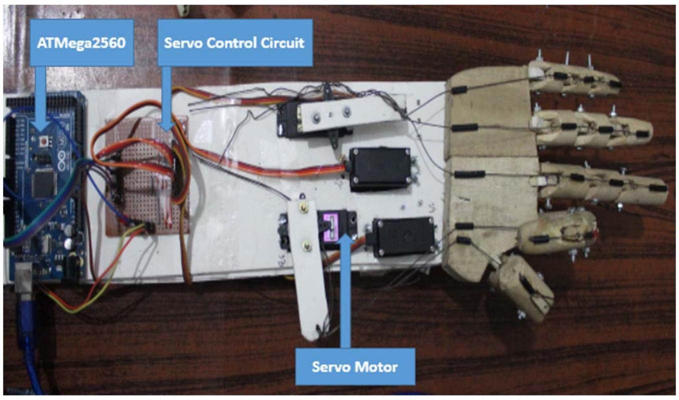

Figure 7. Prototype of prosthetic hand used in this experiment

In experiment, the extracted feature value such as value listed in Table I are feed to nueral network which produces a vector result shown in Table II. In Table III, feature values of traning sample is givien and its corresponding result are listed. The corresponding results indicate that this technique can identify two types of motion and the prototype also able to mimic the corresponding hand gesture.

A. Limitations

The proposed technique is a low-cost prototype which comes with some limitations. The first limitation of this method is that it can only mimic two types of motion which is not enough for flexible daily life prosthetic hand user. Also, this prototype is susceptible to noise. Hence, the performance deteriorates when the prototype is overwhelmed by noisy environment.

V. CONCLUSION

In this paper, the authors have identified only two motions because for more motion classification it requires a signal from 2 or 3 muscle group and additional circuitry is needed. One key feature of this module is real-time implementation. The proposed system requires approximately 0.5sec for motion identification. To extract Emg signal without noise is a challenging task. Due to improper grounding some time external noise is detected which effects ANN’s accuracy. In Future hybrid ANN can be used to detect motion.

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