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DEVELOPMENT OF LOW-COST WIRELESS EMG SENSOR NETWORK

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ABSTRACT

The aim of this work is to design a low-cost wireless EMG sensor network. The design consists of a portable EMG acquisition system and wearable dry electrode unit, which can be applied for monitoring the forearm muscle movement and hence identify the hand manipulation. The system was designed in a way that it could recognize two types of gestures, which are complex hand gestures and normal hand gesture. The performance of the system is evaluated by choosing the best classifier among four classifiers along with 16 features. Among them, the highest classification accuracy obtained for complex hand gesture was about 56% for KNN with VORD feature. For normal hand gesture, maximum classification accuracy was obtained up to 91% for KNN with LOG feature. In addition, the system was experimented on multiple participants by training the classifier and testing the trained model for both the gestures. The system was able to predict hand gesture with decent accuracy.

Keywords: decision tree, K-nearest neighbours, manipulation identification, support vector machine, surface electromyography.

INTRODUCTION

In recent years, surface electromyography (EMG) applications are extensively used in robotic industries to identify the sensitive muscle information to control the prosthetic device, exoskeleton, rehabilitation devices and so on. There are many EMG acquisition systems available with high efficiency of acquiring multiple signals from various parts of the body. Along with the ever so evolving issues of EMG acquisition systems is a large number of wires used to interface between sensor and acquisition leading to a system which is large in size and expensive. Due to these factors commercially available EMG acquisition systems are not feasible in terms of controlling prosthetic device or mobile health monitoring.

Hence, this study proposes a new method of acquiring EMG data, transmitting it wirelessly and finally prototyping inexpensively. Extension-rule based TP method has commended considerable respect from many related researchers.

Most researchers use adhesive electrodes for acquiring the EMG data, but this would not be suitable for wireless acquisition system due to the allergies and also due to long term monitoring. Few researchers have overcome this problem by using dry electrodes instead of adhesive electrode, but application for controlling prosthetic have not been implemented yet, also their design was only for single channel EMG network which can only monitor a single muscle fiber at a time [1]. Feature extraction and pattern recognition for four channel EMG network, which had the ability to recognize four gestures was proposed [2]. The first problem was, the recognized gestures were not as natural as hand gestures and the second problem was that less number of gestures were recognized. The prosthetic control based on the pattern recognition was not approached. The issue of recognizing the patterns of sign language using highly robust pattern recognition algorithm was approached. But this system consists of expensive pieces of hardware such as DAQ (Data Acquisition), transmitter for acquiring the EMG data and the adhesive electrodes [3].

A system was designed as a low-cost EMG sensor network for the purpose of controlling the prosthetic hand. The problem with the system was that the interfacing of EMG electrode and data acquisition system required large numbers of wires. The designed prosthetic hand could only actuate for two finger gestures. Therefore, the improved method of EMG acquisition system would be that the device is wearable by integrating the dry electrodes into wearable device, which gives an advantage of long term monitoring and are reusable [4].

The commercially available prosthetic hands are very expensive, cannot be afforded by wrist amputees in developing countries. Hence, a prototype of low-cost wireless EMG sensor network through which the patterns of hand gestures would be recognized by highly robust pattern recognition algorithm in real-time, would benefit the amputees to accomplish their daily work without any disruption.

METHODOLOGY

The methodology of developing of wireless EMG sensor network is shown in the block diagram in Figure-1, where the steps shows that muscle signals is transmitted to monitor wirelessly and actuate the prosthetic hand based on the recognized patterns.

The placements of the muscles are studied from the musculoskeletal system of the forearm in the posterior and anterior. The selected muscles are flexor carpi ulnaris, flexor carpi radilais, flexor digitorumprofundus and extensor digitoriums.

In order to confirm the identified muscles through musculoskeletal, the method of manually resisting the flexion, extension and abduction of fingers were employed. Based on that, dry Agcl electrodes are integrated into the garment. For amplifying the EMG raw data, the muscle sensor V3 was used. This sensor consist of three main stages, which are pre amplification, filtering and rectification and smoothening. The input signals from the each channels are connected into the TRS jack and the output will be received as a DC signal.

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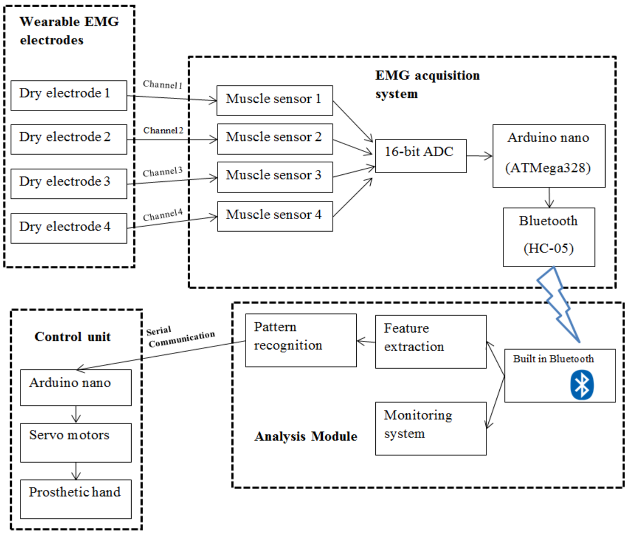

Figure-1. Proposed system block diagram.

Finally, the selected 16 features in time domain were used for testing the pattern recognition models which are integral of EMG (IEMG), mean absolute value (MAV), simple square integral (SSI), Variance of EMG (VAR), Root mean square (RMS), V-order (VORD), Log dector (LOG), waveform length (WL), Willision amplitude (WAMP), Deterministic (DET), average amplitude change (AAC), difference absolute standard deviation value (DASDV), histogram of EMG (HIST), absolute value of third temporal moment (TM3), absolute value of fourth temporal moment (TM4) and absolute value of fifth temporal moment (TM5) are shown in Table-1.

Table-1. Feature extraction methods.

Mathematical representation	Description
$\mathrm{IEMG} = \sum_{i=1}^{N} \lvert x_i \rvert$	Summation of absolute value of EMG signal amplitude
$\mathrm{MAV} = \frac{1}{N}\sum_{i=1}^{N} \lvert x_i \rvert$	An average of absolute value of the EMG amplitude
$\mathrm{SSI} = \sum_{i=1}^{N} \lvert x_i^2 \rvert$	Summation of square value of EMG signal
$\mathrm{VAR} = \frac{1}{N-1}\sum_{i=1}^{N} x_i^2$	An average of square value of the deviation
$\mathrm{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	It is modelled as amplitude modulated Gaussian random process
$\mathrm{TM3} = \lvert\frac{1}{N}\sum_{i=1}^{N} x_i^3 \rvert$	Variation of third order
$\mathrm{TM4} = \frac{1}{N}\sum_{i=1}^{N} x_i^4$	Variation of fourth order
$\mathrm{TM5} = \lvert\frac{1}{N}\sum_{i=1}^{N} x_i^5 \rvert$	Variation of fifth order
$\mathrm{VORD} = \left(\frac{1}{N}\sum_{i=1}^{N} x_i^v\right)^{1/v}$	Non-linear detector the implicitly estimates the muscle contraction force
$\mathrm{DASDV} = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(x_{i+1}-x_i)^2}$	Standard deviation of the wavelength
$\mathrm{AAC} = \frac{1}{N}\sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$	Averaged wavelength (WL)
$\mathrm{LOG} = e^{\frac{1}{N}\sum_{i=1}^{N}\log(\lvert x_i\rvert)}$	Estimate of muscle contraction force based on logarithm
$\mathrm{WL} = \sum_{i=1}^{N-1}\lvert x_{i+1}-x_i\rvert$	Cumulative length of the EMG wave the time segment
$\mathrm{HIST} = \sum_{i=0}^{N} n_i \frac{\text{max intensity}}{N}$	Maximum of the histogram
$\mathrm{WAMP} = \sum_{i=0}^{N} f(x)$	$f(x)\begin{cases}1 & \lvert x_i - x_{i+1}\rvert \\ 0 & \text{otherwise}\end{cases}$
$\mathrm{DET} = \frac{\sum_{i}^{N} lP^{\varepsilon}(l)}{\sum_{i=1}^{N} lP^{\varepsilon}(l)}$	

The four types of pattern recognition used are decision tree, support vector machine and K-nearest neighbour and ensemble classifier.

Schematic diagram of the EMG acquisition system

Figure-2 shows that schematic diagram of the EMG acquisition system. The system consists of four muscle sensors, which are labeled as MS1, MS2, MS3 and MS4. These muscle sensors are connected to the flexor carpi ulnaris, flexor carpi radialis, flexor policies lounges and extensor digitorum. The supply power is given by two nine voltage batteries. These two batteries are connected in series where positive voltage is supplied into '+Vs' terminal of the muscle sensor, the negative voltage is supplied to the '-Vs' terminal and the common node between two batteries is connected to the 'GND' into the sensor. The outputs from the muscle sensors are transmitted to the 16-bit analog to digital converter and then passed into Arduino Nano. Later, the Bluetooth protocol called HC-05 is used to transmit the muscle data wirelessly.

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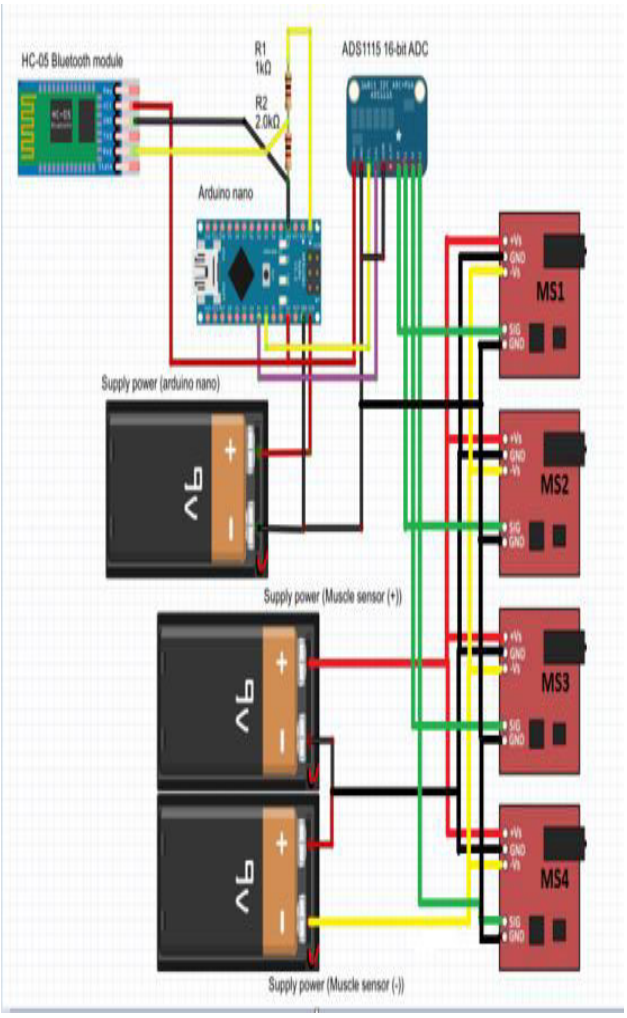

Figure-2. Schematic diagram.

Computer interface

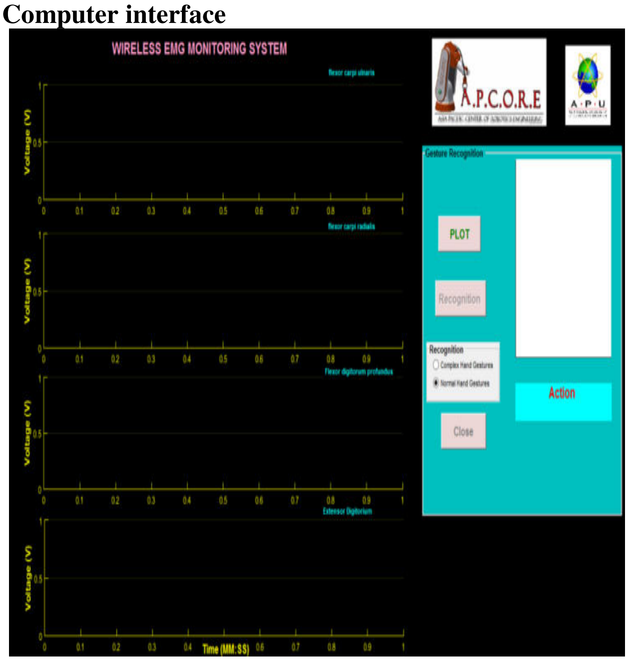

Figure-3. Graphical user interface.

Figure-3 shows the GUI designed for monitoring the four muscle signals. The GUI is designed using MATLAB software. The GUI also consists of the gesture recognition unit, where it can predict two types of gestures in real time. Initially, the acquired signals are plotted on the respective graph upon pressing the PLOT button. After that, gestures can be predicted based on the received signals by pressing Recognition button. Based on the prediction, the gesture type will be displayed on the GUI.

3D printed prosthetic hand

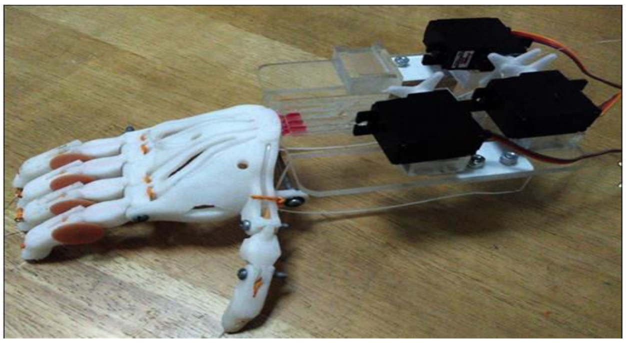

Figure-4. 3D printed prosthetic hand.

The hand was printed using 3D printing technology. The material used for hand is Acrylonitrile-Butadiene-Styrene (ABS). There are three servo motors attached to the thumb, index finger and rest of the three fingers. Each finger has been connected to the servo with the help of an elastic string, which passes through from the finger to the servo motor. In order to give a stable look for the fingers during the inoperative mode, rubber has been attached to the back of the finger.

RESULTS AND DISCUSSIONS

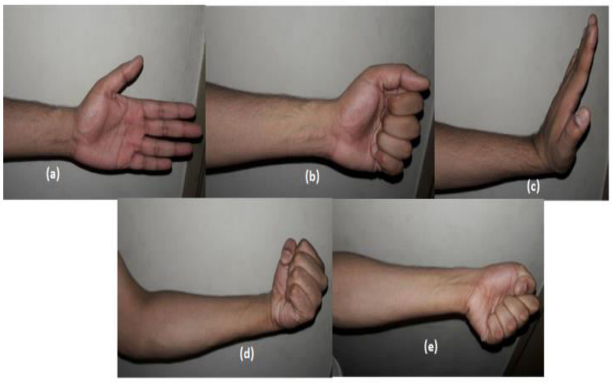

Figure-5. Five hand manipulations.

Figure-5 shows the five types of hand manipulations which are:

a) Opening fist (HO).
b) Close the fist completely without contracting the muscles (HC).
c) Wrist extension (WE).
d) Close the fist and extend the wrist (CWE).

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e) Close the fist, and extend the wrist towards the ulnar (UWE).

The data were collected for single participant of these five gestures and then trained the four classifiers. The obtained classification accuracy is shown in Figure-6.

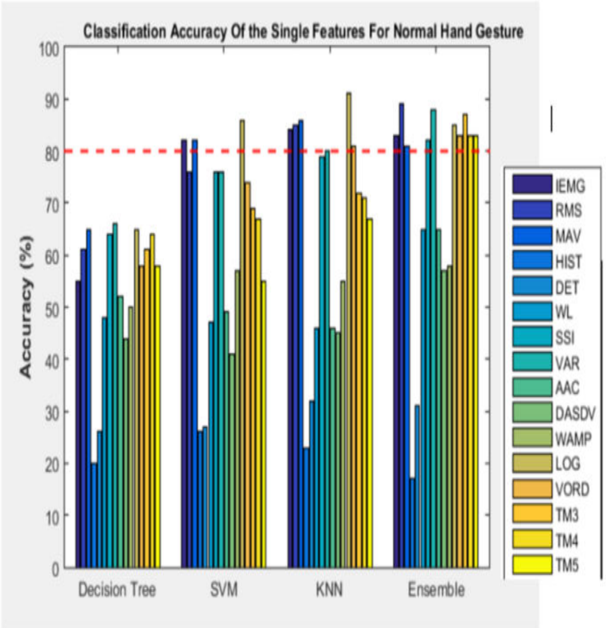

Figure-6. Classification accuracy in percentage.

Based on the obtained results, the K-NN obtained the highest classification accuracy when extracting the raw data using LOG feature, with an accuracy of 91%. The prediction accuracy obtained was decent and further can be improved by replacing the dry AgCl electrodes with better, long lasting electrode.

The trained K-NN classifier was used for recognizing the five types of gesture in real-time from five subjects (Sub1-Sub5). Each participant and his gesture classification accuracy are shown in Table-2.

Table-2. Prediction accuracy.

Target Action	Sub1	Sub2	Sub3	Sub4	Sub5
HO	20	40	20	40	40
HC	40	20	40	20	20
WE	80	100	60	20	60
CWE	40	20	40	20	60
UWE	40	40	40	20	40
Accuracy (%)	44	40	40	24	40

The prediction accuracy obtained was decent and can be improved by replacing the dry AgCl electrodes with long lasting electrode.

CONCLUSIONS

In summary, a low-cost wireless EMG sensor network is designed and developed by having wearable electrode units with multi-channels, portable wireless pocket EMG container. Also, the monitoring system was designed to monitor the four muscle signals wirelessly in real-time. Based on the designed system, it was able to classify five types of hand gestures and able to predict those with decent accuracy.

The future improvement can be done to reduce the prediction time; hence the system can able to predict the hand gestures faster.

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