Control of Upper Limb Prosthesis Using EMG and EEG Signals

Dilruba S[1], Jisha KV[2]

[1]M.Tech Scholar , [2]Assistant Professor , Electrical and Electronics Engineering

Jawaharlal College of Engineering and Technology

Palakkad, Kerala, India

Abstract* - The human hand is a complex system, with a large number of degrees of freedom (DoFs), sensors embedded in its structure, actuators and tendons, and a complex hierarchical control. Despite this complexity, the efforts required to the user to carry out the different movements is quite small. On the contrary, prosthetic hands are just a pale replication of the natural hand, with significantly reduced grasping capabilities and no sensory information delivered back to the user. Bio-signals driven prosthetic hands have been found to be suitable; wherein control is through conveying human's intention to the prosthesis. There are two possible bio-signal based schemes covering the approaches for conveying human's intention to the prosthesis- Electroencephalogram (EEG) based approaches and Electromyogram (EMG) based approaches. EEG based approaches are implemented through an interface between the brain and the prosthetic hand to be controlled. The activity of the brain is recognized based on the EEG signals. Whereas in EMG based approaches, an indirect interface between the brain and the prosthetic hand to be controlled is established based on the muscles' activity through EMG signals.In this paper, the EEG datasets are generated and features are extracted. Here Gamma signals are considered and then classified using Artificial Neural Network (ANN). Further the output is used to control the hand motion. The simulation is performed on Matlab environment. Similarly EMG signals are acquired using Myoware sensor and is used for the control of hand motion.

Keywords—***Electroencephalogram (EEG), Electromyogram (EMG), Artificial Neural Network (ANN)***

I. INTRODUCTION

The role of the hand in human life is not just limited to functional movements, but, rather is essential in communication, sensation and any other area that can be imagined.When a person becomes a limbamputee,

he or she is faced with staggering emotional and financial lifestyle changes. The amputee requires a prosthetic device(s)and services which become a life-long event. A prosthesis is an artificial extension that replaces a missing body part such as an upper or lower body extremity. It is part of the field of biomechatronics, the science of fusing mechanical devices with human muscle, skeleton, and nervous systems to assist or enhance motor control lost by trauma, disease, or defect. An artificial limb is a type of prosthesis that replaces a missing extremity, such as arms or legs. The type of artificial limb used is determined largely by the extent of an amputation or loss and location of the missing extremity. Artificial limbs may be needed for a variety of reasons, including disease, accidents, and congenital defects.

The objective of the project is to develop a prosthetic hand that supplements the basic functionalities of the lost upper limb in amputees. The control to the prosthetic hand is based on the EMG signals extracted from the muscles in the amputee's arm and the EEG signals extracted from scalp. The Electromyogram signals recorded using surface electrodes detects electrical activity related to the user's forearm muscles, thus making it possible to interpret the intention of the subject who acts on the hand by appropriate muscle contraction. The EEG signals recorded using EEG electrode.

With advancements in modern artificial hands more people are interested in new prosthetic hands. This comes at a cost though and usually requires surgery. With the risks of extensive surgery, many patients prefer other options such as skin surface sensor prosthetics. This includes non-implanted electroencephalography (EEG) sensors and electromyogram (EMG) prosthetics which are simpler for patients to control. Due to the simplicity, low maintenance and robustness of older models, most patients still currently prefer the older mechanical prosthetic arms. There are two possible bio-signal based schemes covering the approaches for conveying human's intention to the prosthesis. Electroencephalogram (EEG) based approaches and Electromyogram (EMG) based approaches. EEG based approaches are implemented through an interface between the brain and the prosthetic hand to be controlled. The activity of the brain is recognized based on the EEG signals. On successful recognition of brain's activity; the prosthesis emulate the amputee's intention through the interface. Due to localization of brain activities and multidimensional aspect of the EEG signals, analysis and classification of EEG signals are challenging. Moreover, the appropriate number of channels as well as their specific location on the scalp requires identification. Failing to do so results in degradation of system performance. In EMG based approaches, an indirect interface between the brain and the prosthetic hand to be controlled is established based on the muscles' activity through EMG signals. EMG is the electrical manifestation of the neuromuscular activities and is known to reflect the voluntary intention of the central nervous system. Interpreting the content of the EMG implies the interpretation of the brain's activity to contract a muscle or a group of muscles. EMG based approaches for prosthetic hand control is a targeted reinnervation as it collects information from specific muscles; responsible for specific functions.

II. RELATED WORK

Controlling upper-limb exoskeletons according to human motion intention is not an easy task as well. When controlling an exoskeleton, the selection of a proper control input signal that reflect correct motion intention of the user is really important. So far research is being carried out considering different biological signals and especially Electromyography (EMG) have shown a promising potentials. On the other hand, with the advances of brain signal monitoring methods, Electroencephalography (EEG) signals based control approaches for upper-limb exoskeletons have been gained much attention recently in addition to EMG-based methods.

In H.J LEE et al .of [1] develops a surface EMG interface that employs dry-type electrodes, a single supplied circuit for reduced weight, two voltage followers to improve input impedance, and a modified driven-right-leg circuit using a virtual ground circuit. By adapting a wearable band-type interface. The EMG electrodes can be reused while offering high performance corresponding to that of commercial products. The developed surface EMG system was successfully applied to decode human motion intentions of eight different configurations and a rest condition by using a fast training algorithms in a non-targeted manner.

C.P Shinde of [8] proposes a design of myo electric prosthetic arm. The electrodes are attached to the biceps.The EMG signals generated from a contracting muscle and detected by physiological signal electrodes are first sent to the instrumentation amplifier, the band pass filter, and the precision rectifier circuits. Following amplification, filtering, and rectification, the resulting signals are used as inputs to the microcontroller and are converted to digital ones by a 1-b analog comparator embedded in the microcontroller. According to the digital signals, the program built in the microcontroller can make precise decisions and then output PWM signals to control the R/C servomotor to drive the prosthesis.

Feature extraction for the application of BCI is explained in [19]. EEG signals are recorded from 16 channels and studied during several mental and motor tasks. Features are extracted from those signals using several methods: Time Analysis, Frequency Analysis, Time Frequency Analysis and Time-Frequency-Space Analysis. Extracted EEG features are classified using an artificial neural network trained with the back propagation algorithm. The first analysis method is the Fast Fourier Transform (FFT) by applying the discrete FFT to the signal and find its spectrum.

The relationship between the electromyographic (EMG) and neural signals (ENG) recorded during hand control is investigated. EMG and ENG signals are both recorded from an amputee during the ENG control of a hand prosthesis. The EMG signal was processed with standard techniques to compute the envelope. For the neural signal, the processing involved the evaluation of the energy of the recordings with a moving average and the best combination of window width and multiplier for the standard deviation was searched for. Hence, a new curve for the neural signal was generated, gathering information about amplitude and occurrence of action potentials during the motion task. Its correlation with the EMG envelope was studied by means of a parameter purposely conceived, which accounts for the ratio between the areas under the two curves.To find a correlation between EMG and ENG signals, the action potentials inside the neural recording is detected. Muscle activity is the expression of the intention of the subject to execute a certain movement. Before producing the muscular contraction, the information is given to the fibers through the Peripheral Nervous System (PNS). Hence, it is expected to find a relation between EMG and ENG signals by looking at the amplitude of the EMG and at amplitude and occurrence of the action potentials

III. PROPOSED WORK

Electro biological signals have become the focus of several research institutes, probably stimulated in the findings in the areas of cardiology, muscle physiology and neuroscience. Electrical signals coming from the different part of the body can be used as command signal for controlling mechanical systems.

Electromyography is the measurement of electrical potentials created by the contraction of muscles, when the cells are neurologically activated. The signal so recorded is the electromyogram of the respective muscle. Internally, muscles generate voltages around 100 mV when they contract. These voltages are greatly attenuated by internal tissue and the skin, and they are weak when measured at the surface of the skin. The amplitude of the surface EMG signals for large muscles can range from 0 to 10mV (peak-topeak) .The usable energy of the signal is limited to the 0 to 500 Hz frequency range, with the dominant energy being in the 50-150 Hz range. Usable signals are those with energy above the electrical noise level. These EMG signal can be recorded/measured using surface or needle electrodes, but the electrical signal obtained will be composed of all the action potentials occurring in the muscles underlying the electrode. These signals picked up by the electrode arrangement can then be electronically amplified, conditioned & processed using analog components.

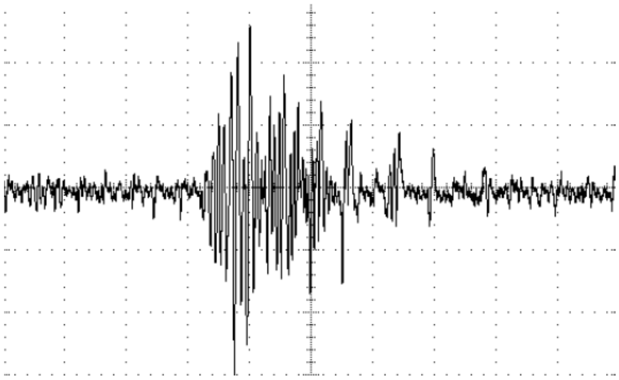

Fig 1 A typical EMG waveform measured during a brief muscle contraction.

The electroencephalogram (EEG) is the depiction of the el ectrical activity occurring at the surface of the brain. This activity appears on the screen of EEG machine as waveforms of varying frequency and amplitude measured in voltage [33]. Electroencephalography (EEG) is the recording of electrical activity along the scalp produced by the firing of neurons within the brain. The EEG can be defined as electrical activity of an alternating type recorded from the scalp surface after being picked up by metal electrodes and conductive media.The International 10-20 System of electrode placement is the most widely used method to describe the location of scalp electrodes.

A. *Development of Prosthetic Hand*

The primary building blocks responsible for the working of the prosthetic hand are as follows:

- Analog signal conditioning unit:
  Performs the signal conditioning and processing on the EMG signals collected by the surface electrodes from the amputee’s forearm muscle. The extracted emg signals are subjected to amplification, filtering and isolation.The final output of the analog signal conditioning unit is a series of short duration impulses that are generated at the onset of muscle contraction.

- Micro-controller unit
  The control signal from the signal conditioning unit is fed to the microcontroller in the form of short duration impulses. Movement of the mechanical hand is based on the programmed algorithm in the Microcontroller. An interrupt triggered programming approach is used for controlling the movement of the mechanical hand.
- Electro-mechanical unit
  The mechanical hand is driven by a servomotor. The controller unit produces pulses of varying lengths, which in turn determines the position it should rotate to. The movement of the motor shaft results in the opening/closing of the hand linked to it.

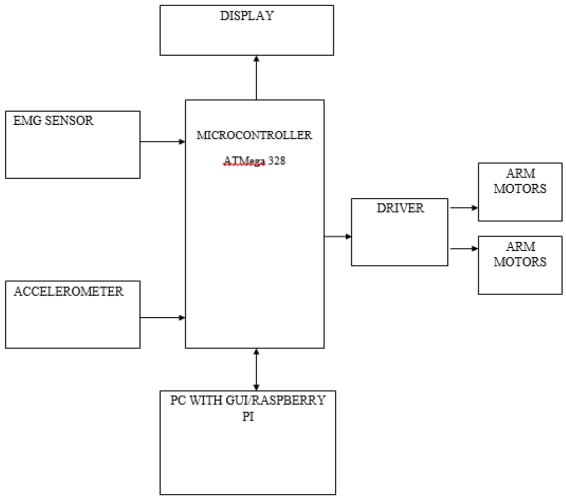

Fig 2 Block diagram of proposed system

a) Accelerometer

This Accelerometer module is based on the popular ADXL335 three-axis analog accelerometer IC, which reads off the X, Y and Z acceleration as analog voltages. By measuring the amount of acceleration due to gravity, an accelerometer can figure out the angle it is tilted at with respect to the earth. By sensing the amount of dynamic acceleration, the accelerometer can find out how fast and in what direction the device is moving.

b) EMG Sensor

The EMG sensor used for this project is called the MyoWare muscle sensor. EMG sensor measures the filtered and rectified electrical activity of a muscle. The output of the sensor is an output voltage that is proportional to the amount of activity in the selected muscle. The electrodes should be place in the middle of the muscle body and should be aligned with the orientation of the muscle fibers.

c) Microcontroller

The Atmega328 is one of the microcontroller chips that are used with the popular ArduinoDuemilanove boards. Atmega328 has 32K of flash program memory and 2K of Internal SRAM.The Atmega328 has 28 pins.It has 14 digital I/O pins, of which 6 can be used as PWM outputs and 6 analog input pins. These I/O pins account for 20 of the pins.

d) EEG data from PC

The EEG potentials were recorded at 10–20 EEG electrode positions over the scalp with a cap and integrated electrodes. These electrodes measure the weak (5-100μV) electrical potentials generated by brain activity. There were 3 files to indicate the details of the dataset. a text file records all the raw data; a 'annot.csv' file records the annotated segments; a 'class.csv' file records the classes. EEG datas were obtained from dataset. This datasets includes 14 records of left and right hand motor imagery. They include 11 channels: C3, C4, Nz, FC3, FC4, C5, C1, C2, C6, CP3 and CP4. The channels are recorded in common average mode and Nz can be used as a reference if needed. The signal is sampled at 512 Hz and was recorded with our Mindmedia NeXus32B amplifier.

e) Servomotor

A servo motor consists of several main parts, the motor and gearbox, a position sensor, an error amplifier and motor driver and a circuit to decode the requested position.

IV. IMPLEMENTATION

Even though, the advances of EMG-based control methods in assistive robots such as exoskeletons are enormous, these EMG-based control approaches used alone have some disadvantages that depend on the user and on the application.With recent advancements of technology, brain machine interfaces (BMI) have attracted a lot of interest in the bio-robotics area. A BMI is a direct communication pathway between the brain and an external device. This device or application can be a simple cursor control program on a computer, intermediate application such as controlling a wheel chair or controlling a complex device such as a prosthetic or an exoskeleton.

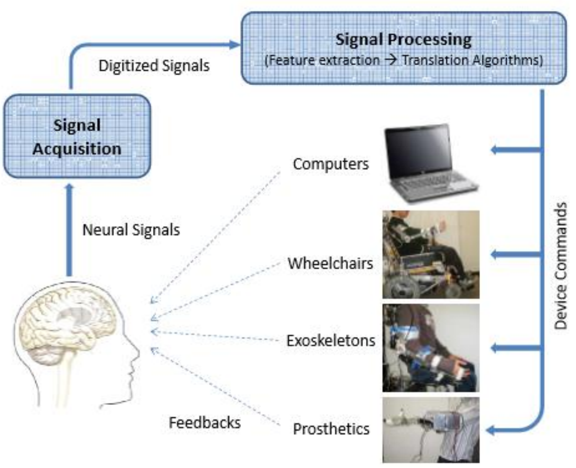

Fig 3 Brain Machine Interface (BMI)

The key technology of BCI is to use the EEG signal of a user and converts the information in it into a control or conversion algorithm of command.

A. Feature Extraction and Classification of EEG signals

The original EEG signal is time domain signal and the signal energy distribution is scattered. The signal features are buried away in the noise. In order to extract the features, the EEG signal is analyzed to give a description of the signal energy as a function of time or/and frequency. The first analysis method is the Fast Fourier Transform (FFT) by applying the discrete FFT to the signal and find its spectrum. EEG signal is non stationary that means its spectrum changes with time; such a signal can be approximated as piecewise stationary, a sequence of independent stationary signal segments.

Formally, classification consists of finding the label of a feature vector x, using a mapping f, where f is learnt from a training set T. In this project, Artificial Neural Network (ANN) is used for classification purpose. Neural networks have the characteristic of self-study, self-organization, and associational memory, parallel processing and distributed storage compared with traditional methods.

For implementing Artificial Neural Networks (ANN) there are three phases: design, training and execution. In the design phase the architecture of the network is defined: number of inputs, outputs and layers, and the activation function of neurons. The training phase consists of determining the weights of the connections of the network through a learning algorithm such as Back propagation. Finally the execution phase is performed using the fixed parameters of the network obtained during the learning phase. Back Propagation BP network is the most famous and activity model in all the feed forward neural networks. Its kernel is the backpropagated algorithm.

B. Hybrid EMG-EEG Correlation

In order to compensate problems with both EEG and EMG based control methods, a combination of both systems, building on the merits of each signal while diminishing the limitations of each might be a promising approach. The main idea behind a hybrid EMG-EEG based control interface is the fusing of EEG and EMG signals in the control method. The fusion of the signals may be carried out in many different ways, and may depend on factors such as the specific application, and the abilities of the users. As a two-input system, a hybrid EEG-EMG approach can either work on the inputs simultaneously or sequentially. Nevertheless, it is important to ensure that, a higher effectiveness is achieved from the fusion approach of EEG-EMG signals, than from methods that use either EMG or EEG signals alone. EMG-EEG correlation is such that making the value of EEG constant and varying the EMG value accordingly. Since the EEG values are obtained from dataset and hence are fixed. The EMG values are obtained real time and vary randomly. To obtain the accurate value of EMG, we use Average Finding Algorithm and Peak Identification Algorithm. . The average EMG is the best method to describe the typical innervation input to an investigated movement or activity.The EMG Peak value is only meaningful for averaged curves because even for smoothed rectified EMG traces, it is still too variable.

The hybrid approaches can improve in several performance criteria such accuracy, reliability or robustness in comparison to individual use of EEG or EMG based control methods. Fusing EMG-EEG control approaches can also improve the potential of assistive robotic applications such as prosthetics and exoskeletons by introducing an additional degree of freedom, and also improves the robustness of the control approaches.

The open-source Arduino software IDE version 1.5.3 for Atmega328P has been used to program Atmega328P for enabling the standalone functioning of the device. Simulation part is done Matlab environment

V. RESULTS

For the proper standalone functioning of the system Atmega 328P was programmed as the main controller and the hardware circuitry was successfully interfaced and tested

A. Analysis of EMG and EEG

The EMG signal is obtained using MyoWare sensor. The output of the sensor is an amplified EMG signal. The amplifier eliminates random voltages caused by electrical noise by subtracting the signals obtained from the ground electrode and the other from the muscle electrode, producing the raw EMG. The rectified EMG signal can be analysed using simulation done in Matlab environment.

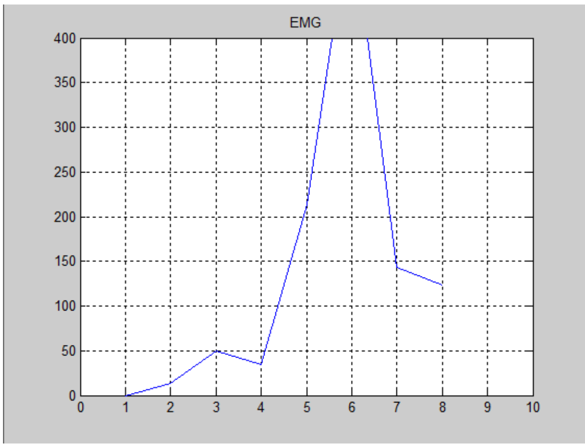

Fig 4 EMG obtained from myoware sensor

For obtaining basic brain patterns of individuals, subjects are instructed to close their eyes and relax. Brain patterns form wave shapes that are commonly sinusoidal. Usually, they are measured from peak to peak and normally range from 0.5 to 100 μV in amplitude.

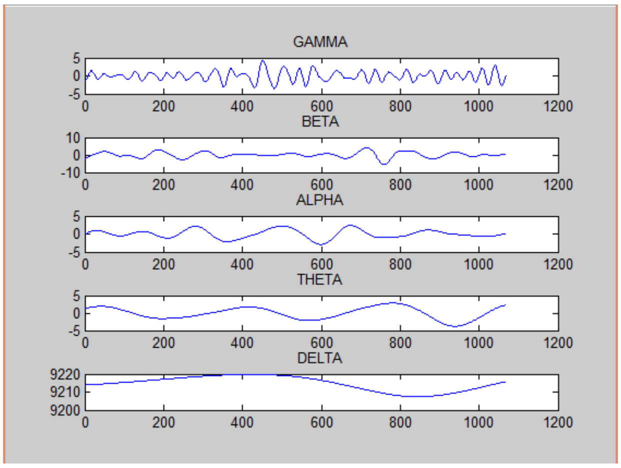

Fig 5 Brain wave samples with dominant frequencies belonging to beta, alpha, theta, gamma and delta band.

B. Control of the arm

The arm is capable of moving its base, elbow flexion and extension, wrist rotation, opening and closing of fingers and pick and place of the object. It controls the limb by performing three activities or tasks. To perform the activity both EMG and EEG must be matched.

- Activity 1 : Full movement of arm with base rotation
- Activity 2 : Elbow movement (Flexion & Extension)
- Activity 3 : Wrist rotation and opening & closing of fingers

Table 1 Condition for doing activities

Condition	Angle	Activity
EMG>200 EEG Classifier 1	90˚	Base rotation and rest of the portion standing still
EMG>150 & EMG<200 EEG Classifier 2	45˚	Elbow motion (Flexion/Extension)
EMG>100 & EMG<150 EEG Classifier 3	90˚	Wrist rotation and opening& closing of fingers

The functionality of the device was tested with people other than the developer. Random testing was performed with 5 male subjects and 3 female subjects of age group 22 – 26 years without any proper training. The summary of the results is tabulated in Table 2 which reveals that even without proper training; the average accuracy obtained is around 67%.

Table 2 functionality of system

Sl No	Sex	Subject	Accuracy in testing the functionality
1	Male	A	99
2	Male	B	80
3	Male	C	70
4	Male	D	20
5	Male	E	99
6	Female	F	98
7	Female	G	20
8	Female	H	50
Average			67

VI. CONCLUSION AND FUTURE SCOPE

It is necessary to control the upper-limb exoskeletons based on the motion intention of the user. EMG and EEG signals have been identified as potential input signals to the control methods of upper-limb exoskeletons since EMG and EEG signals reflect the motion intention of the user. The hand is capable of doing different tasks like elbow flexion/extension, wrist rotation, pick and place, and full rotation of hand. Accelerometers provides variation in direction (X, Y, Z directions), which provide feedback of the system. It ensures whether the system perform in right manner.

The prosthetic hand is controlled by EEG signals and EMG signals. The EEG signals are obtained from datasets of 3 patients and the most promising feature is extracted using fourier transform and it is trained to classify for three movements using Artificial Neural Network. Along with EEG , the amplified EMG is obtained from Myoware sensor which is placed on radii brachii muscles controls the motion of hand. The developed hand is tested with 8 people and found the functionality of the system is 67%.

The prosthetic system of the future should: (i) embed a new generation of control algorithms, able to manage more sensory information(tactile perception ,proprioception ,pain and temperature) and increase hand grasping and manipulation capabilities, (ii) be equipped with a sensory system able to provide reliable information to the hand control, (iii) guarantee a natural control of the prosthesis by establishing a bidirectional communication via neural interfaces, (iv) guarantee stability of the restored tactile sensation for chronic implants.

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