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A Hybrid Approach for Extracting EMG signals by Filtering EEG Data for IoT Applications for Immobile Persons

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Abstract

Brain Computer interface (BCI) is an emerging technology which empowers human to regulate the computer or other electronic gadgets with brain signals. This paper presents an electroencephalography (EEG) based BCI system with filtered electromyographic (EMG) signals for automating the home appliances. EEG signals are usually contaminated by various noise or artifacts which have to be removed in order to correctly interpret the desired output. The system focuses on extracting the EMG signals generated from the hand movement which can be used by a cripple, paraplegic, lame, paralyzed or a person with special need to enhance their independence and increase their capabilities. EEG signals are recorded and filtered out using hybrid digital filters. In this work, the filtered signals are sent to the micro-controller to operate different devices.

Keywords Brain Computing Interface (BCI) · EEG signals · Butterworth filter · Power Spectral Density

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1 Introduction

BCI is a joint effort between a brain and a gadget that empowers signals from the mind to guide some outer action, for example, controlling of a cursor or a prosthetic limb. A direct communication pathway between the brain and the device to be controlled is enabled through the interface [1]. Electroencephalography (EEG) is one of the notable (and maybe the most seasoned among all) brain imaging systems that gives psychological underpinnings of different mind forms, thinking, learning, observation building and emotion arousal [2]. An EEG system uses a non-invasive technology [3] that consist of non-metallic electrodes usually made of carbon and carbon fiber which are placed at the specific locations on the scalp by an internationally accepted system. The electrodes basically measure the difference in voltage which are due to ionic current which moves between neurons and the brain [4]. An electroencephalogram is a test to measure the electrical action of the mind. The system also consist of an amplifier which amplifies the EEG signals as they are of very low amplitude in μVolts.

BCI has been facilitating support to the disabled patients. Getting the instruction from other parts of body and modulating the response of brain giving a channeling support between human mind and technical device. As EEG measures the electrical activity of brain, EMG measures the electrical activity of muscles. Combined with EEG, electromyography (EMG) is utilized to developed better applications for disabled people. For the same, research has been done in past to understand both the signals and differentiate them from each other so that they can be utilized in developing various applications including IoT. A mother wavelet matrix (MWM) is proposed [5] for extracting forearm EMG signals. The aim is to classify these signals for that MWM includes the mother wavelet which has the highest difference between two classes. In [6], a coherence approach to estimate the consistency of EEG and EMG signals is proposed, which will help in classifying the hand movements easily. For estimating EEG and EMG coherence, EEG sapling is performed and then moving average of the samples is taken. And finally the EEG signals relevant to muscle movements are taken. Some of the few methods which involves extraction of EMG signals from EEG are using Empirical Mode Decomposition (EMD) and calculated Time-domain (TD) features [7], discrete wavelet transform [8–11], convolution neural network [12]. In an other work, surface electromyogram (sEMG) signals were extracted for designing o0f prosthetic hands. Initially, a variant of PCA is applied for removal of noise and then a tunable Q-factor wavelet transform (TQWT) is used for feature extraction [13].

The purpose of this paper is to devise an efficient means for filtering EEG signal from all other signals except for the EMG signals which will be further used for IOT application such as smart parking for differentlyabled person [14]. Figure 1 shows the system design to be followed in this work. The major artifacts which are present in EEG signals are ocular artifacts, muscle movement artifacts and the noise due to appliances present while recording the data, such as fan. The paper is structured as follows. Various terminologies discussed in the proposed work are described in Secti. II. Section III describes data acquisition procedure. The proposed architecture is explained in Sect. IV. Section V discusses the proposed application. In Sect. VI, simulated results are presented. Finally, Sect. VII concludes the work.

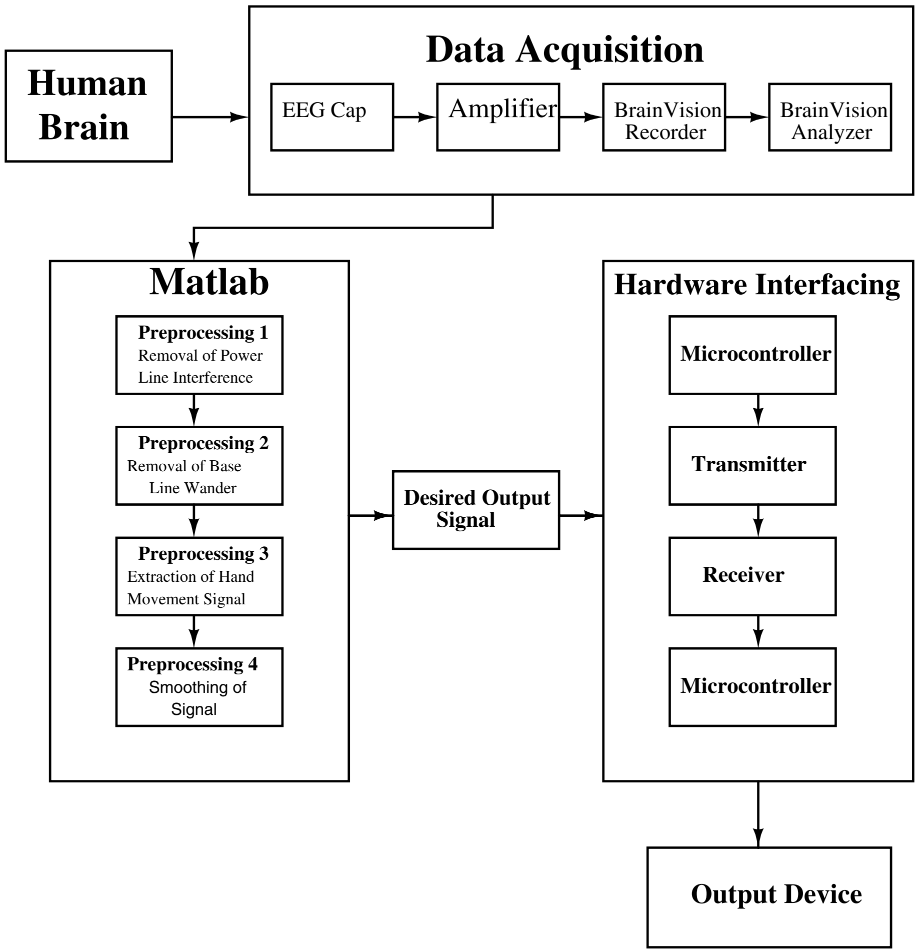


Fig. 1 System Design

2 Terminology

2.1 Filters

For obtaining artifact free signal, it need to be preprocessed. The task of preprocessing is done by the conditioners of signal which are known as filters. These filters works by taking the signal as its input, removing the unwanted or undesired frequencies which are predefined to it, and finally passing out the remaining signal to the output. Filters are broadly classified into two categories. The first are digital filters which are put into action by a digital computer or by a specific motive digital hardware. While the other are analog filters, which are implemented as a circuit using electronic components such as resistors, capacitors, inductors and also consisting of energy source, such as an operational amplifier. Therefore, the analog filters are known as Hardware Driven Filters and the digital filters are known as Software Driven Filters. Analog filters or Hardware Driven filters again classifies into two categories passive filters and the active filters. As our project contains the preprocessing of a signal through a computer software Matlab R2017a which is a proprietary programming language and multi-paradigm numerical computing environment developed by MathWorks. So, we are going to cover the digital filter part rather than analog filters. Digital Filter or Software Driven Filter is generally an execution of a function on a sampled discrete-time signal to decrease or increase specific features of that signal in a computer application. Digital Filters are further classified depending on the type of frequency response, which are as follows:-

2.1.1 Low-Pass Filter

Low-pass Filter [15] let the low frequency pass through it while stopping the part of signal whose frequency crosses the specified threshold value. Basically a low pass filter only permits the signals having low frequency from 0 Hz to the specified cut-off value

2.1.2 High-Pass Filter

Contradicting to low-pass filter, the High-pass filter only permits the signals having high frequency than its specified cut-off [16]. High-pass Filter is also known as Low-cut filter.

2.1.3 Band-Pass Filter

Band-pass filter [17] allows a specific band of frequency to pass through it without touching rest of the signal and not adding up any other additional unwanted signal in it. The band of frequency which passes through the filter can be of any width and is generally termed as the filter bandwidth. Band-pass Filter is also known as the cascaded output of a low-pass and a high-pass Filter.

2.1.4 Notch Filter

Band stop filters [18] stops the band of signal having frequencies between the specified two cut-off values and let go the frequencies on both the sides of the domain of cut-off values prespecified to it. When this band is extremely narrow and greatly attenuated over a particular frequency then filter is mentioned as the Notch Filter. The ideal frequency response of a notch filter is

$$H(e^{jw}) = \begin{cases} 0, & w_0 \\ 1, & \text{otherwise} \end{cases}$$

here w_0 is the frequency to be eliminated. While the real transfer function of a Notch filter

$$\mathrm{H(s)} = \frac{s^2 + w_0^2}{s^2 + 2w_c s + w_0^2} \tag{1}$$

where w_0 is the middle stopped frequency and w_c is the range of the stop band.

Digital Filters are also classified on the basis of impulse response which are FIR Filters (Finite Impulse Response Filters) and IIR Filters (Infinite Impulse Response digital Filters). The description of these filters are given below.

2.1.5 FIR Filters

FIR stands for Finite Impulse Response [19] digital filter, impulse response of FIR filter is of limited duration, reaching value of zero in finite duration is an outcome of it. The output of FIR filter is calculated as an addition of previous, current and upcoming input values.

$$\mathrm{y[n]} = k_0 x[n] + k_1 x[n-1] + \cdots + k_q x[n-q] \tag{2}$$

when the above equation is simplified

$$\mathrm{y[n]} = \sum_{m=0}^{q} \mathrm{k}_m \mathrm{x[n\text{-}m]} \tag{3}$$

q is finite in above equation. From the above equation it is clear that FIR filters are based on feed-forward function which indicates that there is no input of previous or upcoming outputs in the formation of current output. The transfer function of FIR filter [20] is

$$\mathrm{H(n)} = \sum_{n=-\infty}^{n=\infty} h[n].z^{-n} \tag{4}$$

Here, z is the complex variable and H is the Z-transform of the impulse response. Periodic frequency response lies in the area bounded by the circle having radius of unity and is centered at the origin. This region is defined by z= e^{jw}, $-\pi < w < \pi$.

2.1.6 IIR Filters

IIR stands for Infinite Impulse Response [21] digital Filter. Unlike the FIR Filters, these have infinite impulse response and consists a connection of feedback for the formation of output. Therefore, they are also referred as recursive digital filters. The response of these filters in frequency domain is considerably more than that of FIR Filters with same order. Following equation shows the recursive part participation

$$\begin{aligned}\mathrm{y[n]} &= \frac{1}{p_0}(q_0 x[n] + q_3 x[n-3] + \cdots + q_a x[n-a] \\ &= -p_0[y] - p_3 y[n-3] - \cdots - p_b y[n-b])\end{aligned} \tag{5}$$

When the above equation is compressed and regrouped

$$\sum_{j=0}^{b} p_j y[n-j] = \sum_{i=0}^{a} q_i x[n-i] \tag{6}$$

After taking Z-transform on both the sides of equation and putting the values of input and output in transfer function, the transfer function of IIR filter becomes,

$$H(z) = \frac{\sum_{i=0}^{a} q_i z^{-i}}{1 + \sum_{j=1}^{b} p_j z^{-j}} \tag{7}$$

Where,

– a represents forward feed filter order

- q_i are the forward feed filter coefficients
- b is the feedback filter order
- p_j are the feedback filter coefficients
- *x[n]* is input to the filter
- *y[n]* is output from the filter

2.2 Power Spectral Density (PSD)

The vehemence of the energy as the function of frequencies is depicted by power spectral density function [22]. It demonstrates at which frequencies the variations are strong and at which they are weak. The unit of PSD is energy (variance) per frequency (width). PSD is an important parameter which helps to check the suppression of noises in the signal. The dispersion of the signal power over frequency is represented by the periodogram power spectrum estimate. A direct estimate of the frequency content of the signal can be made from the spectrum. PSD can be calculated as:

$$S(f) = \frac{1}{FsN} \left| \sum_{n=1}^{N} x_n e^{-j^{2\pi f/Fs^n}} \right|^2 \tag{8}$$

where Fs is sampling frequency. The periodogram is nothing but an estimate of the power spectral density(PSD) of the signal which is defined by the sequence [x1, x2, x3, ..., xN]. To compute the PSD it uses a n-point FFT.

3 Data Acquisition

3.1 Equipment

The equipment to obtain EEG signal data consist of an EEG cap i.e. ‘Easycap’, which is a 32 channel EEG standard cap and V-Amp amplifier which allows to record signals with a sampling rate up-to 5000 Hz and a broad hardware bandwidth ranging from DC to 1000 Hz and has 16 channels, 1 reference, 1 ground and 2 AUX port. It can be easily connected to the computer via a USB connection and powered up with the same having on board TFT-display, software controlled AC/DC-coupling, impedance measurement. An abrasive electrolyte gel is used for conductivity. The software used are BrainVision recorder and BrainVision analyzer.

3.2 Experiment

To avoid any external noise and disturbances the subject is made to sit comfortably in a silent room. Any movement other than the experiment can result in unnecessary moderation in the signals. The cap is placed on the head of the subject such that it fits perfectly. The 10/20 International system [23] is adopted for the location of electrodes to be placed. Electrodes are placed on brain scalp using an electrolyte gel, which improve conductivity of the electrode (Fig. 2).

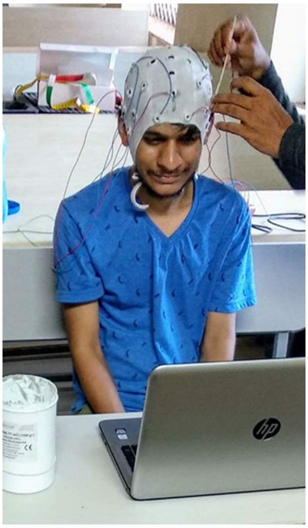


Fig. 2 Setup

Channels C3, C4, F7, F8, Fz and Cz are used based on their functionality. After attaching the electrode to the EEG cap the data is recorded which is sent to the computer through an amplifier.

The EEG signals are obtained by an experiment conducted on eight healthy male subjects aged between 18 and 22 years without any abnormalities. In experiment, a video of 29 s is shown to do a certain task on particular time such as eye movement, hand movement, jaw movement etc. as shown in Table 1. Electrode impedance is kept below 10 KΩ for good EEG recording. Signals are amplified and sampling rate is 250 Hz.

4 Proposed Approach

BCI based home automation for an immobile person is proposed in this project. Prototype of a wearable device is built to examine a operation consisting of hardware and software part which functions through the brain signals, delivering a specific actual running system. This prototype is taking EEG signals as an input and output can be any home appliance that user wants to control. Output device can be connected to the user either through Bluetooth, Wifi or over internet [24]. Working of this prototype can be compared to any model

Table 1 Scenario of the experiment

Time (s)	Activity
0–5	Nothing
5–8	Eye blinking
8–13	Nothing
13–16	Right hand movement
16–21	Nothing
21–24	Jaw movement
24–29	Nothing

which takes values from the sensors and provides output to an actuator. The electrodes present on the EEG cap are behaving as the sensors taking input from the brain then these signals passes through a sequential process where unwanted signals and noises are eliminated which proceeds further to a microcontroller. Here the device which is connected to microcontroller is acting as a actuator which turns ON and OFF on the wish of user. The proposed architecture is given in Fig. 3

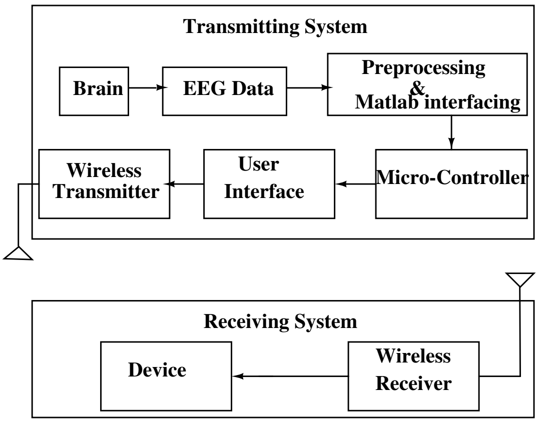
4.1 Result of Hardware Interfacing

Various Microcontrollers can be interfaced with Matlab from which we have selected Arduino Mega which is based on ATmega 1280, when the signal completes all the preprocessing levels the output amplitudes at different time intervals of the waveform is stored in an array. An algorithm is prepared which executes framed commands which runs over a restricted number of times beginning from the initial value to final value over the array passed to it. A threshold value is defined in the algorithm which is automatically set when a number of data recordings is passed, a mean value of all these passed recordings is stored in a variable which then acts as a break off value. The data recordings which are passed in the algorithm belongs to the same subject and depending upon different subjects value of threshold varies. If a value in an array comes up which is greater then threshold the algorithm reaches to stage where it passes the HIGH value to microcontroller's digital output pin and device connected to it gets turn ON.

4.2 Preprocessing

Examination and understanding of EEG signals are challenging as these signals are jeopardize of varying unwanted signals. Many methods have been formulated for avoidance and elimination of noises. In this paper, a combination of filters for removal of noises from the recorded brain signals have been applied, to improve the signal quality for further analysis. The EEG signals from an individual's brain acts as an input to the designed hybrid filter which filters out the noise from it and provides the desired outcome. The noises which are filtered consists of power line interference, artifacts from eye blinking, base line wander, electrode contact noise and jaw movement artifact.

Fig. 3 Proposed architecture



4.2.1 Preprocessing 1: Power Line Interference Removal

Various artifacts affect the EEG signals, the most usual is power line interference. Power line interference [25] can be simply identified as there is a interruption of a voltage of frequency 50 Hz in the recorded data. Power line interference takes place because of imperfect contacts on the subject's cable and also due to unclean electrodes. If the electrode cap or the subject is not correctly grounded, then power line interference may entirely contaminate the EEG signal. Whereas the occurrence of power line interference mostly occurs due to the detached electrode which causes sturdy interrupting signals and consequently requires a immediate work. For removal of this 50 Hz power line source a 2*nd* order notch IIR filter is designed with sampling frequency of 256 Hz. As notch is a specific filter with a high dismissal rate only for a little frequency band around the chose frequency. It won't affect the other different frequencies which have a place in the EEG signal. The System Eq. 9 of this Notch Filter is:-

$$H(z) = \frac{(z - e^{jw_0})(z - e^{-jw_0})}{(z - re^{jw_0})(z - re^{-jw_0})} \tag{9}$$

In the above equation, e^{jw_0} and re^{jw_0} are individually for capturing zeros and poles. By simplifying the above equation using Euler's formula i.e putting the value of $e^{jx} = cosx + jsinx$ then

$$H(z) = \frac{1 - 2cosw_0 z^{-1} + z^{-2}}{1 - 2rcosw_0 z^{-1} + rz^{-2}} \tag{10}$$

From Fig. 3, it is clear that there is an interference of 50 Hz frequency in the recorded signal which is to be removed before proceeding the data for further analysis. After passing the signal through notch filter the input and output data through power spectral density using Welch's method and Hamming window has been analyzed. From the Fig. 4, the output data is free from power line artifact. The signal is also analyzed with

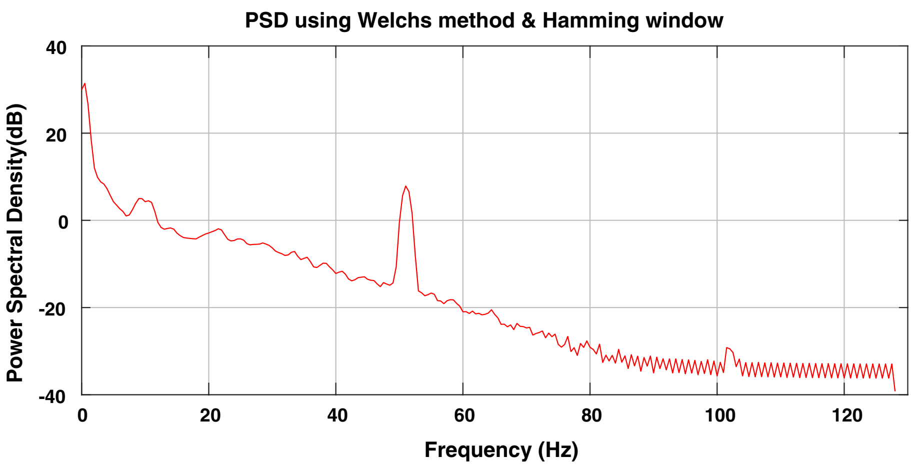


Fig. 4 Power Spectrum Density with Power line artifact

PSD via Periodogram and Hamming window the result of which is shown in Figs. 4 and 5 is for the input signal having power line artifact.

4.2.2 Preprocessing 2: Removal of Baseline Wander

Along with the power line interference, base line wander [26] also observed normally in the recording of EEG signals. This artifact can be caused by breathing, varying cathode impedance, movement, change in temperature and disturbance in the equipment too. For the perfect observation of recorded data this unwanted noise is to be removed. The least complex technique for removal of this artifact is to pass the EEG signal through a high pass filter that restricts this drift from the signal. Base line wander have frequency under 0.8 Hz, therefore the filter is typically set to a cutoff value of 0.8 Hz.

After passing the signal from Notch Filter the signal is then passed for Base Line Wander removal. Figures 5 and 7 are showing the input from two subjects, Figs. 6 and 8 shows the output of Chebyshev [27] high pass filter which is set at a cut-off frequency of 0.8 Hz.

4.2.3 Preprocessing 3: Extraction of Desired Frequency Channel

A high pass and low pass butterworth IIR filter [17] along with zero-phase shift(filtfilt) having cut off frequency at 20 and 30 Hz respectively are implemented for obtaining the desired frequency channel for the extraction of EMG signals. Selection of order is also important. Also the phase information are modified by non-linear phase IIR filters like Butterworth filter but by applying zero-phase IIR filter the effect on phase is minimized to a certain extent. So in Matlab while designing an IIR filter its coefficients are designed with the function “filtfilt” instead of “filter”, to minimize the non-linear phase effect. Also a window based filter will not perform well for a narrow frequency band. Frequency response [17] of a generalized “N” order butterworth filter is

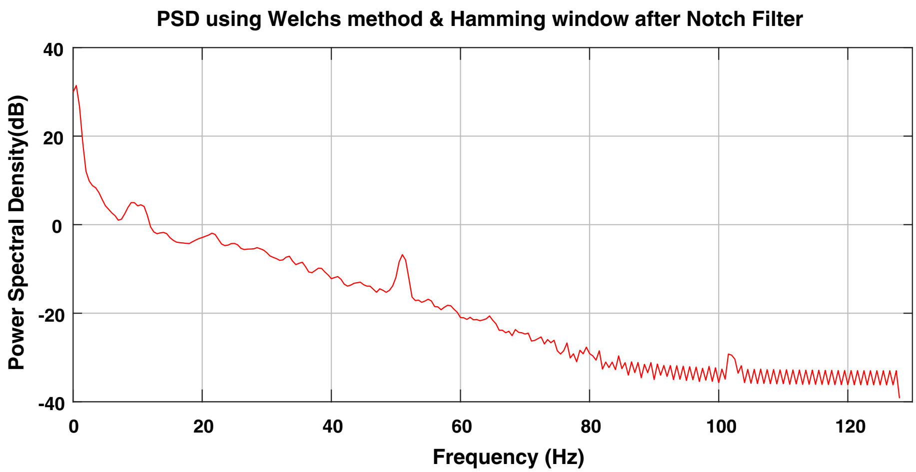


Fig. 5 Power Spectral Density after Power line interference removal

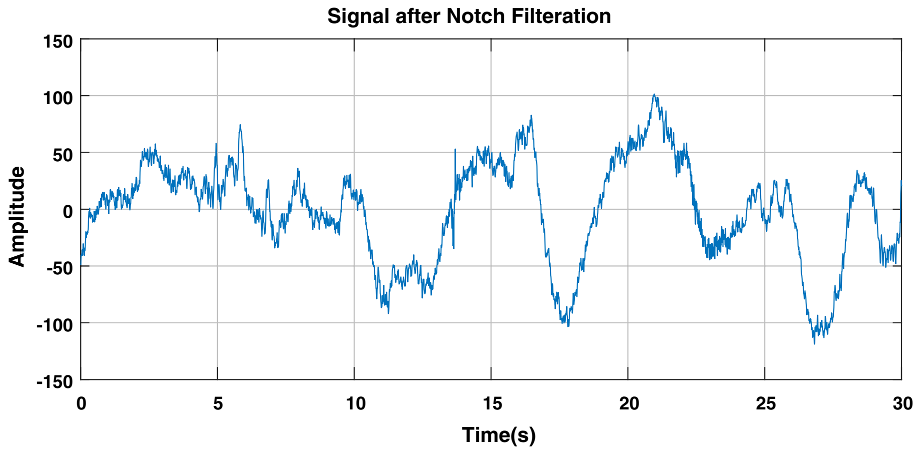


Fig. 6 Data recorded from subject 1

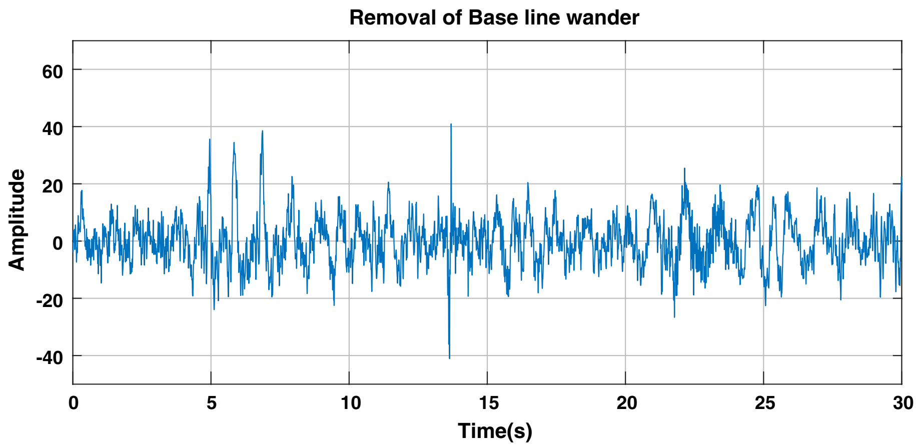


Fig. 7 Base Line Wander Removal

$$H(jw) = \frac{1}{\sqrt{1 + \epsilon^2 \left(\frac{w}{w_p}\right)^{2n}}} \tag{11}$$

The normalized transfer function of a high-pass and a low-pass Butterworth Filter [28] is:

$$H(s) = \frac{1}{(s+1)(s^2 + 0.618s + 1)(s^2 + 1.618s + 1)} \tag{12}$$

5th order Butterworth low pass and high pass filter are the cascaded form of One 1st order and two 2*nd* order filter butterworth low pass and high pass filters respectively. Figures 9 and 10 shows the data of Subject 1 and Subject 2 respectively, which has already passed through two preprocessing stages and it indicates that when we pass the signal through 5th

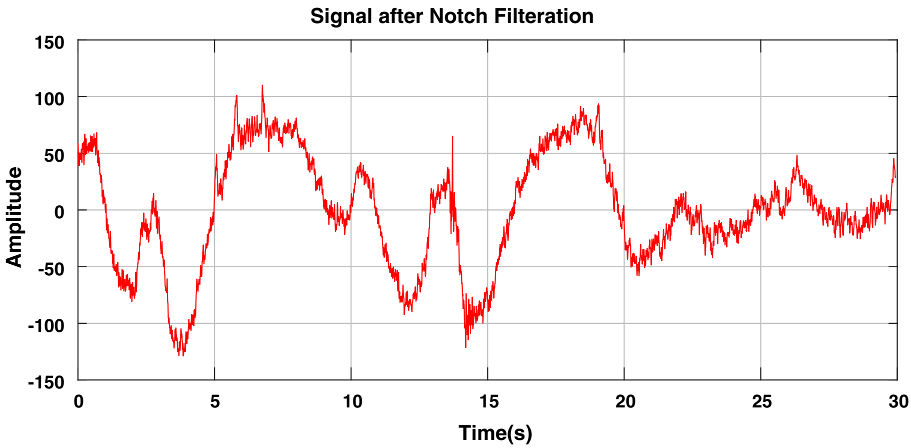


Fig. 8 Data recorded from subject 2

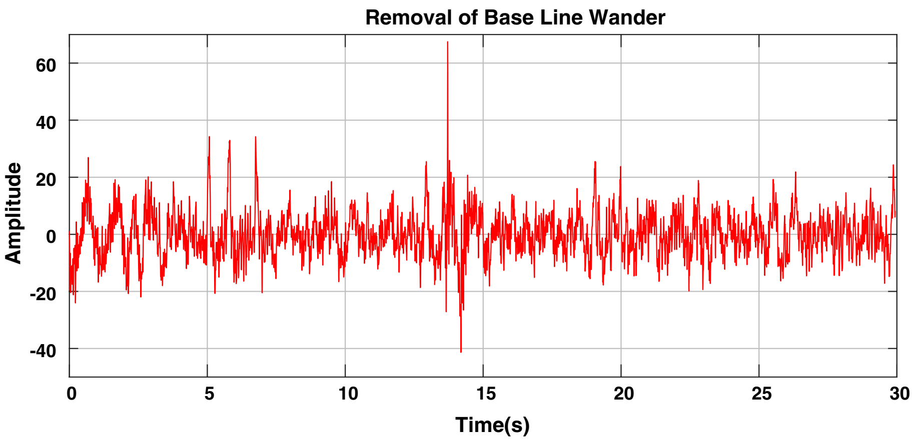


Fig. 9 Base Line Wander Removal

order butterworth high pass and low pass filter the EOG artifacts and Jaw movement artifacts get filtered out (Fig. 11).

4.2.4 Preprocessing 4: Smoothing of Signal

After passing the signals through the above described preprocessing steps, the signal we obtain is free from the defined artifacts. There are some random noises which still remains in it, for elimination of these random noises and for getting a smooth time domain signal, moving average filter [29] is used as it is easy to implement and it work as a low pass filter. For getting the signals which is free from ringing or overshoot and for a improved stop band attenuation we have passed the signal through the designed kernel window moving average filter. As the name suggests, the moving average filter

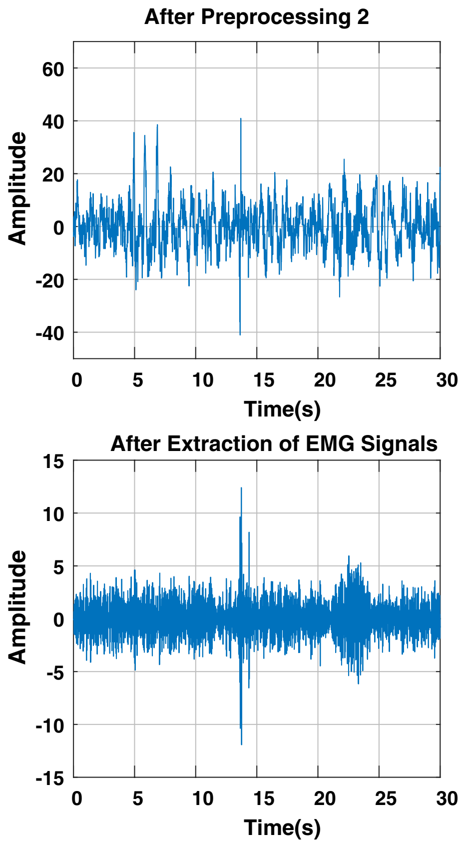


Fig. 10 Subject 1

yields each point in the output signal by averaging a number of points from the input signal (Fig. 12).

It is given by the equation:

$$y[i] = \frac{1}{M} \sum_{j=0}^{M-1} x[i+j] \tag{13}$$

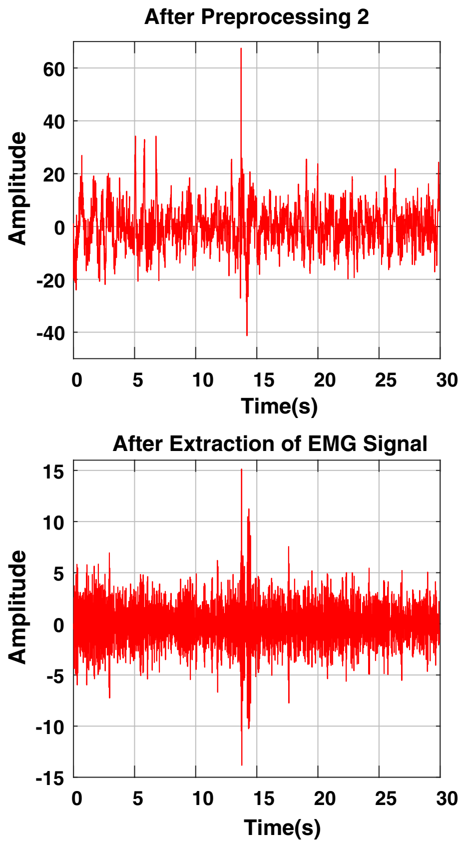
Where

- x[]= input signal
- y[]= output signal
- M= number of points in the average

The frequency response of the moving average filter is given by the formula and is mathematically described as the Fourier transform of rectangular pulse.

$$H[f] = \frac{sin\,(\pi f M)}{Msin\,(\pi f)} \tag{14}$$

Fig. 11 Subject 2



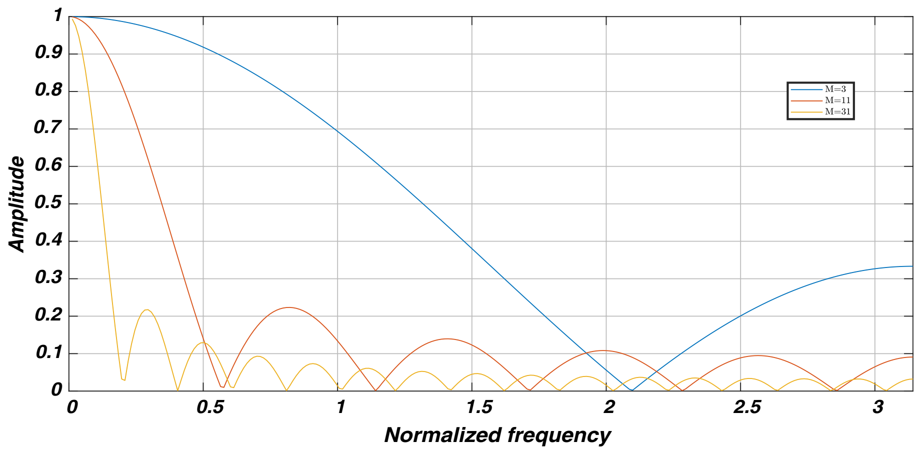


Fig. 12 Frequency response of Moving Average Filter at different at various values of M

The frequency response analysis of the moving average filters show that the 11 point averaging is suitable for the designed hybrid filter. The frequency response of the filter is not good, but for the application of smoothing a signal it does not matter. The key thing to see is that the initial zero occurs at f = 1/N. The idea to determine order of filter which is appropriate to smooth out the components over a particular frequency is given by the graph. The amplitude of the output signal comes to zero when the value of normalized frequency $2\pi/f_s$ is approximately equal to 0.5.

5 Filtering Result

On executing the above designed filters on EEG data with different artifacts recorded by the BrainVision kit, the following outputs are obtained which clearly shows that the right hand movement signals are filtered out from the raw EEG signals having different kind of artifacts. Figure 13 shows the raw EEG data of 3 subjects for eye blinking, right hand movement and jaw movement. In the raw data the presence of power-line interference, baseline wander and the change in signal's peak for eye blinking, right hand movement and jaw movement can be clearly seen. The raw signals are then passed through above described filters and the output wave-forms are obtained which is as shown in Fig. 14.

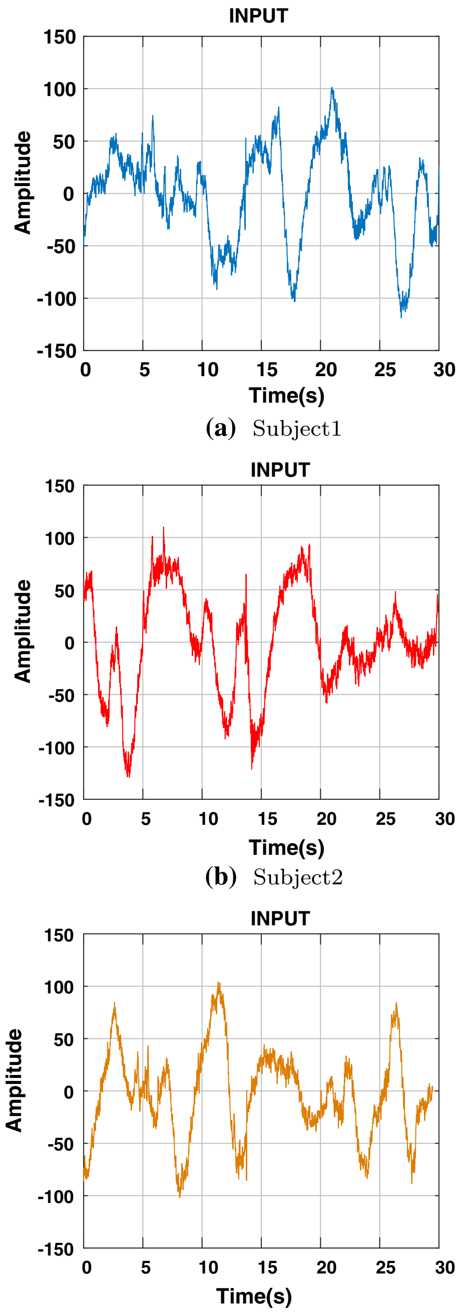
The output wave-forms shows that the power-line interference of 50 Hz has been removed along with the baseline wander and the peak for the desired output i.e right hand movement can be classified easily from all other signals. The EOG artifacts and the EMG artifacts from the jaw movements are removed. From the analysis in Matlab it was observed that the time at which the peak was obtained is according to the experiment and the maximum power of the signal at a particular frequency also occurs in the desired frequency range. The time for occurrence of the hand movement peak and the maximum power of the signal at a particular frequency which was observed from the Power Spectral Density(PSD) analysis are as shown in table:2.

The output signals are shown in Fig. 14 for 3 different subjects in which the EMG signal can be easily distinguished from the remaining signal.The frequency range for hand movement is between 20 Hz to 30 Hz and the PSD analysis of the final output signals shows that the maximum frequency of the signal of subject 1,2 & 3 is 21.4,21.8 & 21.5 which lie in this frequency range. This shows that the remaining artifacts and signals other than the hand movement signals are removed and the EMG signals to be extracted for the specified application are extracted out. The time for the hand movement in the experiment was between 13-16 second and the analysis on Matlab showed that the peak in the filtered signals of subject 1, 2 & 3 occurred at 14.01, 14.12 & 14.69 respectively. This proves that the peak are of extracted hand movement signals (Table 2).

6 Discussion

The research going in the field of cognitive neuroscience gives a new path to develop more interactive brain and computer interfaces which can convert human neural reactions into the control signals for devices [30]. The system consisting of hardware and software enables the user to communicate with external world. There are number of BCI applications such as medical application, neuroergonomics and smart environment, neuromarketing and marketing, educational and self-regulation, games and entertainment, security

Fig. 13 Raw EEG data



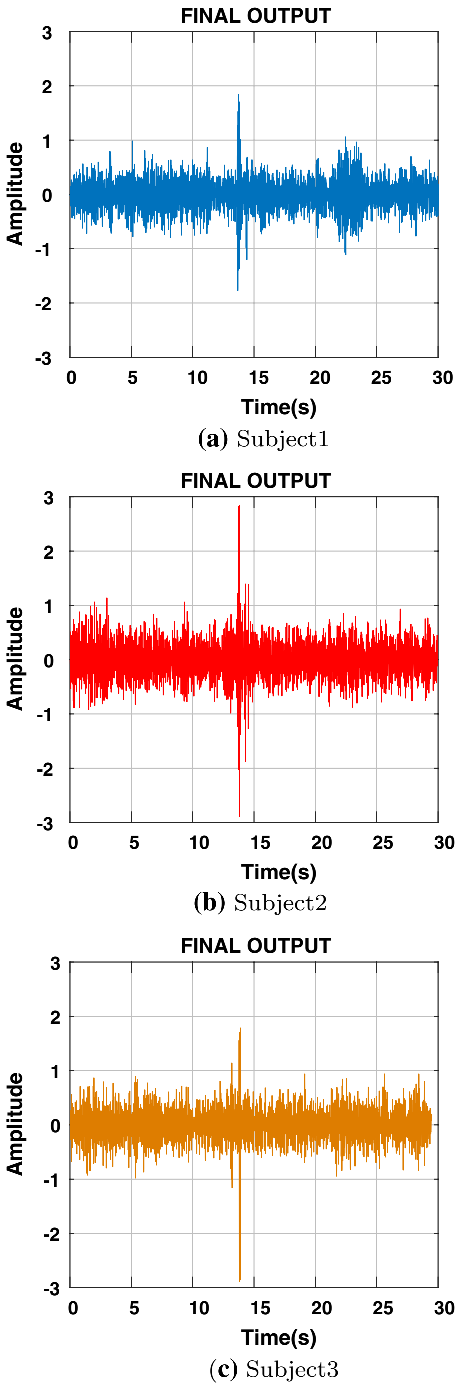
(a) Subject1

(b) Subject2

(c) Subject3

and authentication etc [31]. It is expected that over 50 billion devices will be connected to the internet by 2020. The rapid growth of the Internet of Things(IoT) is believed to upgrade ability and impact numerous domains such as home automation, health-care,

Fig. 14 Filtered EEG data



(a) Subject1

(b) Subject2

(c) Subject3

Table 2 The time and power of peak generated while hand movement

Subject	Time(s)	Power(Hz)
Subject 1	14.01	21.4
Subject 2	14.12	21.8
Subject 3	14.69	21.5

manufacturing and industries and transportation etc. BCI is coming forth as a futuristic alternative to support the interaction between an individual and the IoT objects. BCI is mostly used for bio-medical application for assistance devices to increase the independence of physically challenged or locked-in users [31] but the BCI system can also be used by a other users also. The idea to control a device with brain has always been fascinating. In this paper we present an idea for home automation using BCI so as to reduce the day to day life difficulties faced by a person with disabilities. Through this system a user can control home appliances by just a simple hand movement without moving from his place. This system will not only increase the independence of the a disabled person but will also provide assistance to the elderly person and it can also be used in smart homes [32].

7 Conclusion

In this paper, we have proposed a system to remove noises from EEG signal and to extract EMG signals of right hand movement for the IoT based home automation application to provide an assistance to disabled persons. EEG data was collected using electrode cap with the help of software BrainVision recorder and the raw data was converted into mat files using BrainVision analyzer.The filtration,extraction and analysis of EEG data consisting of hand movement was done in Matlab. A hybrid filter consisting of 2nd order IIR Notch Filter, Chebyshev High Pass Filter with cutoff 0.8 Hz, Butterworth High pass and Low pass filter with zero phase shift having cutoff 30 Hz and 20 Hz and a Moving Average Filter were compiled, the artifacts were removed and EMG signals for hand movement were extracted. The filtered signals after extraction were then used as a input signal to a microcontroller which was interfaced with Matlab and it can be connected over internet for IoT applications. Further a wearable system consisting of filters to extract a particular data of the brain can be made having a real time application without any hindrance, which can be used in day to day life of a person in need.

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