Survey on Home Automation System Using Brain Computer Interface Paradigm based on Auditory Selection Attention

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Abstract – *A direct communication link can be created between a human brain and external device using Electroencephalogram. This used a technique called brain computer interface. Brain computer Interface (BCI) is one of the communication channels used to make interaction between human brain and digital computer to control/operate the external devices without having any touch of muscular body part. This can be implemented for a smart home system as an remedy to help individuals suffering from speech and motion related disabilities. This provides the easiness in operations and also helpful to elder and disable people. This is useful for people who cannot operate the peripheral devices using normal muscular body parts. This system consists of an ultra-cortex headset, Arduino boards, speakers, personal computers with processing IDE, SD card module, and proximity sensors. Electroencephalograms (EEGs) were averaged for each stimulus type, and event related potentials (ERPs) can be obtained.*

***Key Words*: Auditory Steady State Response, Brain Computer Interface, Electroencephalogram, Integrated Development Environment, Home Automation**

1.INTRODUCTION

We know that a physically handicapped would be in short of a physical or sensory functionality. This is deteriorating the interaction or no interaction at all with their surroundings. Thus, leading to considerable inconvenience. Activities of normal people prove to be near impossible feats to them. A simple action of switching on a light would be challenging for such individuals.

Two methods of obtaining EEG signals for a BCI exist: invasive and non-invasive EEG. In the non-invasive approach we just use an external sensor for acquiring the brainwave signals. In the invasive EEG method, signals are captured by electrodes surgically implanted within the depths of the brain. In non-invasive EEG, the signals are acquired from the surface of the scalp by the sensors designed to capture EEG signals. By using the non-invasive EEG method, the signals from the brain in response to an auditory stimulus can be captured by placing a set of electrodes on the auditory cortex, which is located in superior temporal gyrus of the temporal lobe. However, these signals cannot be interpreted without suitable computing procedures as the signal acquisition is not as effective as in the invasive method. In our model we use non-invasive approach of brainwave acquisition, where we demonstrate the switching functionality of two appliances that is, a LED GLS light bulb powered by an AC power source and a fan. The switching operation of these two components are achieved by a relay.

Brain Computer Interface (BCI) has given the opportunity for people who suffer from speech and motion related conditions such as Aphasia, Aphronia, Arthritis, Hemiplegia, Palsy, Paraplegia, as well as other motor neuron related diseases. BCI not only take advantage of advancements in home automation technology but also improve the overall quality of life for individuals who are suffering from speech and motion related conditions. BCI is a method of communication with a computer using the electroencephalogram (EEG) signals obtained from the user's brain activity. Considering EEG signals are independent of the normal pathways of the nerves and muscles, EEG signals can be used to implement a home automation system. The home automation system design uses a BCI to capture EEG signals, convert these signals into analyzable data, and then turn these signals into useful inputs that can be used to operate a home automation device that is easy to use and is independent of voice control from the user. There are several papers that propose to use BCI as a method to operate home automation devices. A home automation system using two responses, a Steady State Visually Evoked Potential (SSVEP) and the eyeblink artefact is presented in. In this method, the authors use a visual stimulus to control a home automation system. Emotive EPOC uses three built-in suites to determine the various types of signal inputs based on emotions.

1.1 Purpose: Significance/need of chosen topic

The field of BCI research and development has focused primarily on neuroprosthetics applications that aim at restoring damaged hearing, sight and movement.

Fig -1: Neuroprosthetics

Thanks to the remarkable cortical plasticity of the brain, signals from implanted prostheses can, after adaptation, be handled by the brain like natural sensor or effector channels. Following years of animal experimentation, the first neuroprosthetic devices implanted in humans appeared in the mid-1990s.

1.2 Scope of the topic

BCI technology may be used for thought-to-text translation or to control movements of a prosthetic limb. The umbrella term BCI covers invasive BCI, partial invasive BCI and non-invasive BCI. Invasive BCI includes the implantation and use of technology within the human body, such as surgically placed electrodes to directly detect electrical potentials. Partial invasive BCI devices are external recorders that detect signals from superficially implanted devices. An example of partial invasive BCI is electrocorticography (ECoG), which records activity of the brain via an electrode grid that was surgically embedded.

BCI research intends to restore and enhance neural features of the central nervous system by linking it to a computer system. In conclusion, BCI has progressively achieved several monumental milestones. The future impact of BCI in terms of patient care is slowly starting to come into focus. It is important to remember that the generation of physicians that we belong to will be in charge of knowing and integrating new technology, to provide better care to our patients.

2. LITERATURE SURVEY

[1] Using Brain Computer Interface for Home Automation

Brain computer interface (BCI) is a communication pathway between the brain and the external peripheral devices like computers. We propose to use this technology for Home automation. Home automation can be totally revolutionized using BCI. Brain produces various types of waves like alpha (9-13Hz), beta (14-30Hz), theta (4- 8Hz), delta (1-3Hz). Using these waves, we can control various home appliances. The entire concept consists of 4 main stages detection, amplification, processing, output. First detecting the brain signals using an EEG cap or electrodes. These brain signals are very weak hence in second stage we need to amplify these brain signals to a usable amount and filter these to remove noise. Then thirdly, we will have to convert these signals into digital by using A to D converter and into a type a computer software or a microcontroller can understand. Fourth, taking this decoded signal and sending these signals wirelessly, by using an RF circuit to a distant switch circuit, which will turn on or off the appliance in vicinity. Using this technology, the life of people would be further simplified, physical efforts would be considerably reduced and it would also prove as a boon for physically disabled people.

[2] Brain Controlled Home Automation System

Brain Computer Interface (BCI) is one of the communication channels used to make an interaction between human brain and digital computer to control/operate the external devices without having any touch of muscular body part. This provides the easiness in operations and also helpful to elder and decibel people. This is useful for people who cannot operate the peripheral devices using our normal muscular body parts. The proposed system aims to control home appliances (like bulb, fan etc.) with the help of Human Attention Level which comes under non-invasive method of brains signal measurement. This attention is being measured by NeuroSky Headset. Attention level values are ranges from 1 to 100. Attention means user's level of mental focus which occurs during intense concentration and directed (but stable) mental activity. So, to get attention values user should observe the object (or focus onto the object). For demonstration purpose here are used one bulb and one fan.

[3] Smart Home: Toward Daily Use of BCI-Based Systems

Smart home technology can improve the quality of life for inhabitants of homes. This technology allows the inhabitants to monitor their home and any electrical device locally or remotely via computerized central control. Despite the advances in the smart home technologies, people with disabilities - particularly those with quadriplegia, - will not be able to utilize the currently available techniques. Thus, Brain Computer Interfacing (BCI)-based smart home systems are effective control mechanisms for people with disabilities; since it allows them to cope and adapt with the existed technologies. BCI systems are based on human brain signals instead of physical actions, therefore, people with disabilities will be able to control their house independently. In this paper, a BCI-based smart home system is developed to allow a person who suffer from quadriplegia to open/close doors using brain signals only, which will reduce their need for caregivers. Emotiv Epoc+ was used to detect the user's brain signals. Furthermore, two different suites from Emotiv—the Cognitive Suite and Facial Expressive Suite— were used and tested to deliver the milestones of this technology for people with disabilities. Accordingly, the results of the two suites were analyzed in terms of training time, the ease of generating signals, detection efficiency and user preference to determine which suite is suitable for daily use. Moreover, two prototypes for the developed system were implemented.

[4] A controllable home environment for the physically disabled using the principles of BCI

A Brain Computer Interface (BCI) is a new form of communication established between the human brain and a digital computer. The main prioritized goal of the project is to allow a severely disabled person to control the surrounding home appliances from their situated place, with massively reduced requirement for movement. It offers an alternative to natural communication and control. For every thought, action or interaction of a person, a unique Event Related Potential (ERP) is generated in the brain as a result of various neurons being active. This mutual interaction of multiple neurons results in the development of a miniscule electrical discharge. Using an appropriate brain-wave sensor, we can resolve these electrical signals and associate them to proper driving operations using suitable computing procedures. Hence, even a person who does not have any control over the motor functions of his organs can seamlessly command and control the electrical appliances present in his abode

from his seated place. Using currently available computing and electronic technologies, we demonstrate a prototype model where we control two electrical appliances, an LED GLS bulb
and a CPU fan which represents the function of a typical appliance fan. Using MATLAB, we code the functionality of how the controlling action of the two appliances happen.

[5] Classification of Motor Imagery for Ear-EEG based Brain-Computer Interface

Brain-computer interface (BCI) researchers have shown an increased interest in the development of ear electroencephalography (EEG), which is a method for measuring EEG signals in the ear or around the outer ear, to provide a more convenient BCI system to users. However, the ear-EEG studies have researched mostly targeting on a visual/auditory stimulus based BCI system or a drowsiness detection system. To the best of our knowledge, there is no study on a motor-imagery (MI) detection system based on ear-EEG. MI is one of the mostly used paradigms in BCI because it does not need any external stimuli. MI that associated with ear-EEG could facilitate useful BCI applications in real-world. Hence, in this study, we aim to investigate a feasibility of the MI classification using ear-around EEG signals. We proposed a common spatial pattern (CSP)- based frequency-band optimization algorithm and compared it with three existing methods. The best classification results for two datasets are 71.8% and 68.07%, respectively, using the ear around EEG signals (cf. 92.40% and 91.64% using motor-area EEG signals).

3. METHODOLOGY

3.1 Hardware, Design and Experimental Setup

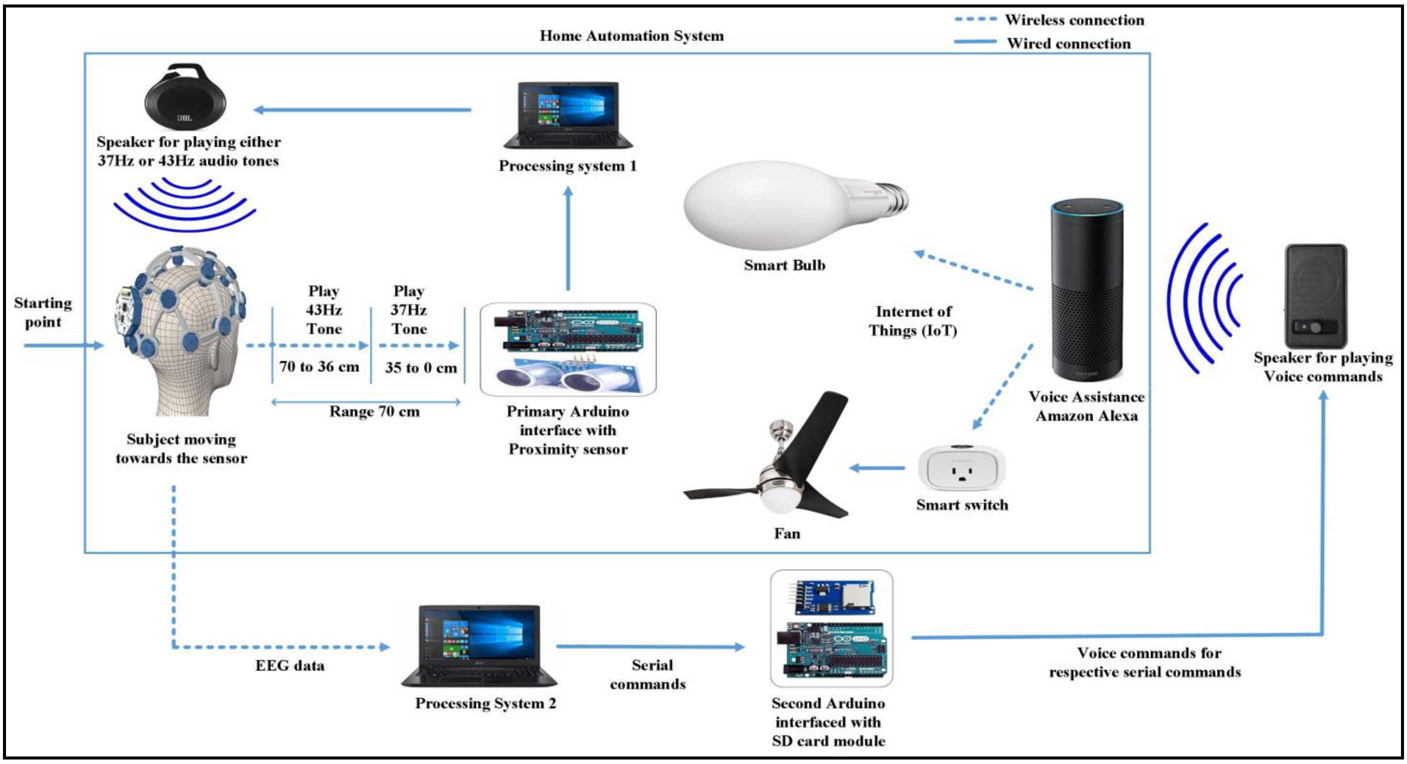


Fig -2: Block diagram of home automation system based on auditory steady state response using OpenBCI interface

The BCI based home automation system presented comprises of an OpenBCI board with electrodes and an ultra-cortex headset, primary Arduino interface with proximity sensor, secondary Arduino board with an SD card module communicating serially with the EEG processing IDE, and a voice-controlled device. The system starts with the primary Arduino equipped with a proximity sensor. Based on the distance of the subject from the sensor, a tone is generated. After a tone is generated, the OpenBCI board attached to an ultra-cortex headset (with electrodes) collects EEG signals from the subject at specific locations of the brain. The collected EEG signals are filtered and used to determine the serial command sent by the processing IDE to a secondary Arduino. Depending on the serial command sent, respective voice commands, stored in an SD card module, is played on speakers. The voice-controlled device (Alexa) detects these voice commands and performs the action intended on either a smart bulb or a smart plug attached to a fan.

A. OpenBCI V3 board, electrodes and Ultra-Cortex headset

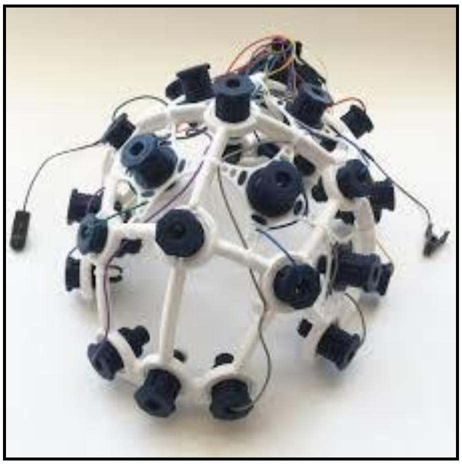


Fig -3: Ultra-cortex headset setup

Fig 3 shows the Ultra-Cortex headset, with a version 3 OpenBCI data acquisition board attached, which will be placed on the subject's head. The OpenBCI data acquisition board is an 8-channel neural interface with a 32-bit processor sampling at a rate of 250 Hz. Data can transmit wirelessly from the board to a computer for processing with the help from an RFDuino radio module integrated onto an OpenBCI USB dongle. Electrodes of the headset are positioned on the scalp according to international 10–20 measurement standards to acquire proper EEG signals. The position of the electrodes is as shown in Fig 4.

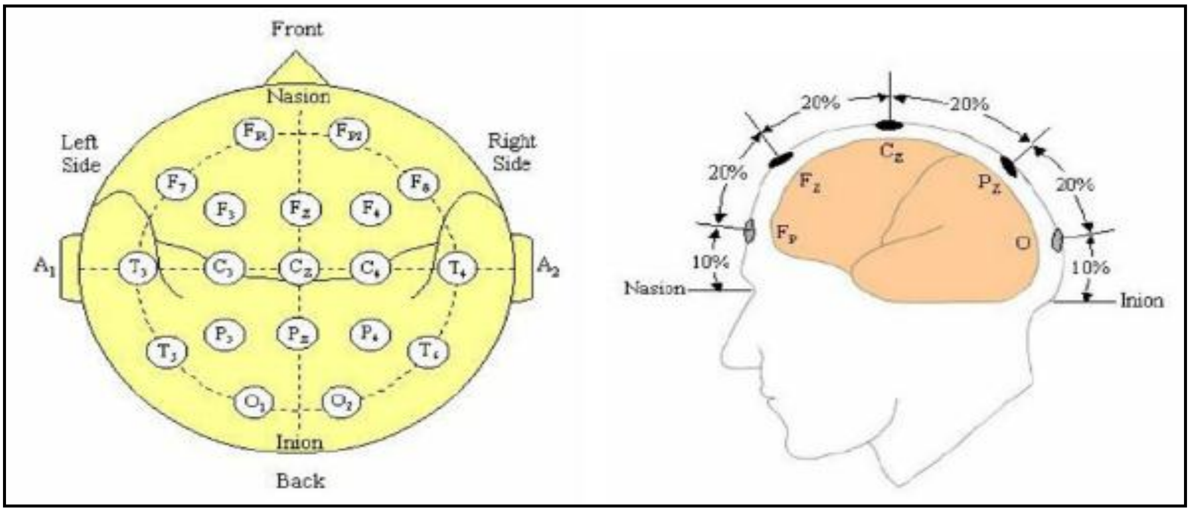


Fig -4: Electrode position

Data is collected from parts of the brain by connecting an OpenBCI channel, corresponding to a pin on the board, to an electrode. Two channels of the OpenBCI board are used to extract EEG data from the positions T3 and T4 of the 10-20 system shown in Fig. 4. The EEG data is filtered and passed through a Fast Fourier Transform (FFT) so components such as EEG signal peak and signal-to-noise ratio can be derived. This information is used to determine the validity of a detection. Two electrodes are attached to the ear lobes for a bias and reference point.

B. Home Automation System Setup

The set up as shown in Fig. 5 consists of the following modules and processes:

1) Audio Tone Generation

Previous tests demonstrated that system response time often ranged between 10 to 30 seconds. Mono-toned square shaped waveforms are generated with a frequency of 37 Hz and 43 Hz and amplitude of 1 V using Audacity software. To match prior tests, these waveforms are then recorded in a noise free environment for 30 seconds and converted into .wav format to make them compatible with the wireless stereo speakers. These wireless stereo speakers are placed at a comfortable distance to allow the subject to listen and concentrate on the tones.

2) Primary Arduino Interface with Proximity Sensor

An ultrasonic sensor (HC-SR04) with range of detection from 0m to 5m is connected to the primary Arduino board to provide the current distance of a subject with respect to the sensor. If the subject is within a redetermined range, a 37 Hz or 43 Hz tone can be generated by means of a request to the processing IDE to allow the tones to be generated on computer's wireless speakers. Two varying ranges, one from 0 - 35 cm and one from 36 - 70 cm, will trigger 37 Hz and 43 Hz frequencies respectively. Ranges were determined by dividing the max distance by the number of tones (two tones, in this case) As long as the subject does not move out of range, a distance of 0 cm to 35 cm from the proximity sensor generates a 37 Hz tone for 30 seconds at a time. If the subject moves between 25 - 35 cm away from the sensor, a 43 Hz tone is immediately generated for 30 seconds, overriding the 37 Hz tone if it is still generating. Both 37 Hz and 43 Hz tone frequencies generate repeatedly, but not simultaneously, while the subject is within the sensor's range.

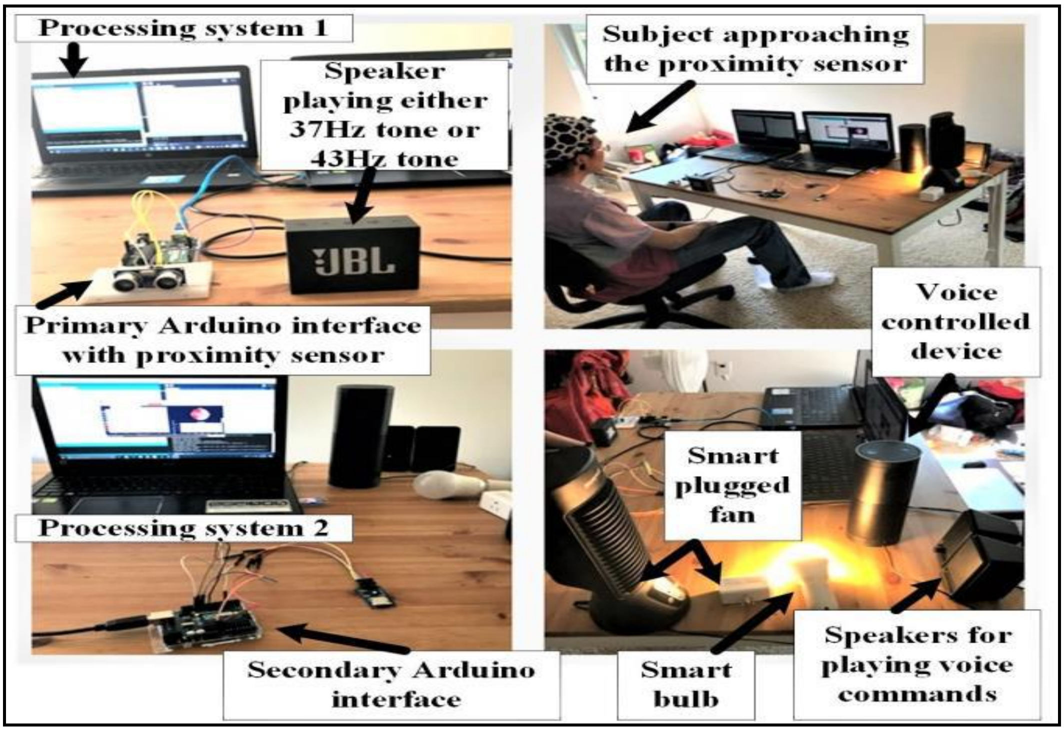


Fig -5: Experimental setup

3) Secondary Arduino interface

Once EEG data acquired from the OpenBCI board is processed using the processing IDE, on a second personal computer, commands are sent serially to the secondary Arduino Uno board equipped with an SD card module. Each of these serial commands are assigned to voice commands such as "Alexa! Turn on the fan", "Alexa, Increase the brightness of the bulb by 25%". These voice commands are preloaded within the SD card module. When a particular action is signaled, its serial command is sent and its corresponding voice command is played through a speaker connected to the module. Voice commands, rather than electronic activation, allow simple integration with current existing devices on smart hubs such as Google Home and Amazon Alexa.

4) Voice Controlled Device

Alexa is a voice controlled personal assistant developed by Amazon. This device is capable of voice interactions and can be configured to control devices like bulbs, fans, garage doors, thermostats, etc. These devices interact with Alexa in a common network using a Wi-fi router. Configuration is set up using the Alexa application and TPlink Kasa application. Once Alexa is set up, it can accept voice commands from the speaker and perform intended actions such as turning ON/OFF, brightening, and dimming the bulb.

C. EEG Processing

Fig 6 depicts processing of raw EEG data and the procedure to convert it into useful commands. Channels 6 and 7 of the OpenBCI board are assigned to T3 and T4 locations on the ultra-cortex headset. The EEG data is extracted from these channels and sampled at the rate of 250 Hz.

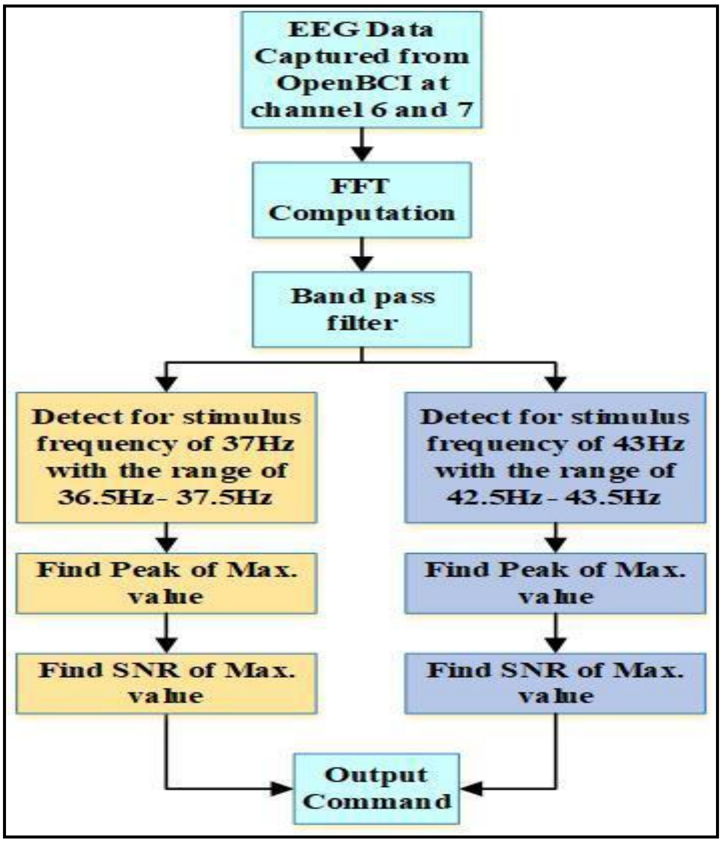


Fig -6: Flow chart of EEG processing

This sampled data in time domain is converted into frequency domain by applying a Fast Fourier transform (FFT) algorithm. This helps in stabilizing and detecting peak values of the signal. Once the signal is fully stabilized by the

FFT algorithm, three conditions must be satisfied for it to be considered a detection: detection range, signal-tonoise ratio (SNR), and a sufficient EEG peak. Filters on the OpenBCI board are used to set detection range. Only EEG signals yielding frequencies ranging from 36.5 to 37.5 Hz and 42.5 to 43.5 Hz is considered for 37 Hz and 43 Hz respectively. Signal to noise ratio (SNR) involves the relative peak, measured in µV, with respect to the average noise, also measured in µV, in the background.

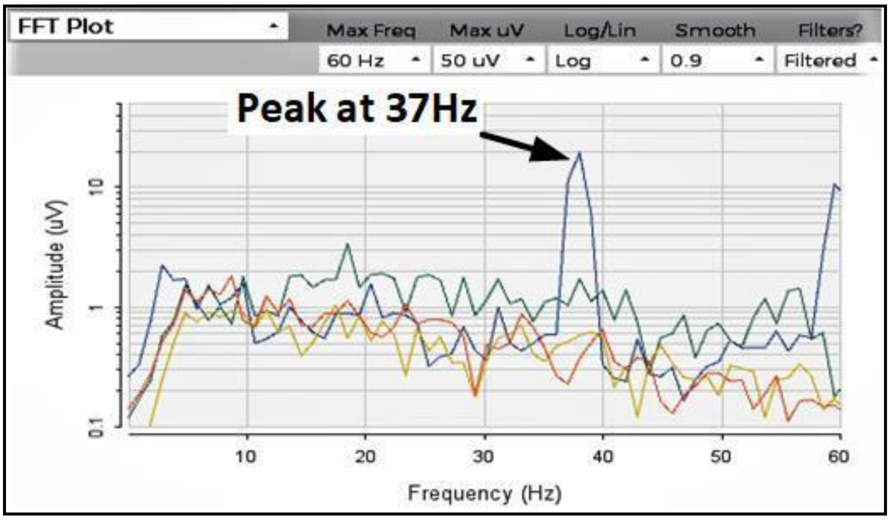
Threshold value of SNR is set between 5 to 7.5 depending on the individual. Only a signal with an SNR higher than the threshold will be considered.

Minimum EEG peak is the minimum threshold value that the EEG signal must reach to be considered a detection. A minimum EEG peak helps eliminate the possibility of presenting a false high signal to noise ratio (i.e. low signal of .0005 uV with a lower average noise level of .00001 uV results in an SNR of 50, making for false detection). Minimum EEG peak threshold is set between .001 to .003 µV based on an individual's response. Detections will be sent serially to the secondary Arduino denoting which voice command should be played. A graphical user interface allows for visual observation of peaks detected at 37 Hz and 43 Hz.

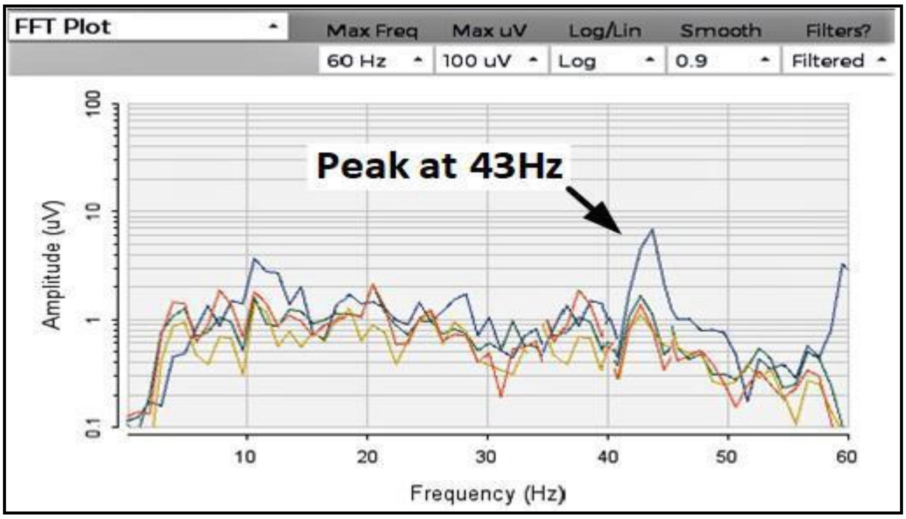
3.2 Technique and design

Possible states for the light bulb and smart plug are shown in Fig 8. With the exclusion of the pending state, each state will return to the initial state following execution of its respective voice command (i.e. from the "turn on" state, it will return to the initial state automatically). Following each return to the initial state, system response time is recorded and the subject is tested for another state in the system. Time taken to complete a task is recorded in each step if its system response time is less than 150 seconds. Compared to other frequencies, the 37 and 43 Hz frequencies referenced in the system state flowchart (Fig. 6) provide distinguishable difference in frequency and viability as a means of detection compared to other tones. Frequency response of EEG signal data, measured in in µV, at 37 Hz and 43 Hz are shown in Fig 7(a) and Fig 7(b) respectively.

Its frequency axes represent EEG signal data. The curves over frequency represent the various electrodes on the headset, each collecting EEG data. Of these curves, the highest are from electrodes T3 and T4. Since each individual will respond differently to the 37 Hz and 43 Hz tone, preliminary testing is conducted to measure the strength of their response. Based on the individual response, the detection rate is regulated so that detections are not too frequent or infrequent to maintain an average rate of one detection for every 15 seconds.



a) 37 Hz Peak detection



b) 43 Hz detection

Fig -7: Frequency response of EEG signal data

Maintaining an average rate synchronizes it with data collection, since a set of EEG signals will only be accepted once every 15 seconds according to design to prevent issues with the processing IDE (such as crashing). Once preliminary testing is completed, the subject starts data collection by concentrating. on a 37 Hz frequency tone activated by the proximity sensor (while in the initial state of Fig 8). Following this procedure, the lightbulb will turn on (entering the “turn on” state of Fig. 8).

The subject is asked to respond again to the 37 Hz tone in the same manner to enter the pending state. After this, they are asked to attempt to trigger first an additional 43 Hz tone to dim the light bulb (by entering the dim state). Soon after, the subject is asked to create and respond to a 37 Hz frequency tone (pending state) and respond to another 37 Hz frequency tone to brighten the light bulb (brighten state). In each step, detection times are noted. Finally, the 43 Hz tone is triggered by each subject in the initial state (as noted in the state diagram of Fig 8) to turn on the device attached to the smart plug and then return to its initial state. The subject then responds to another 43 Hz peak in its initial state so it turns off the device attached to the smart plug (in this case, a fan). Upon completion, the data collected (time for each action, if present or not) is used to assess accuracy of the OpenBCI system. Viability is assessed with average time for individual detection (each state) and the accuracy of detection (yes or no, whether or not it is the right command). The full setup used to collect data is shown in Fig 5.

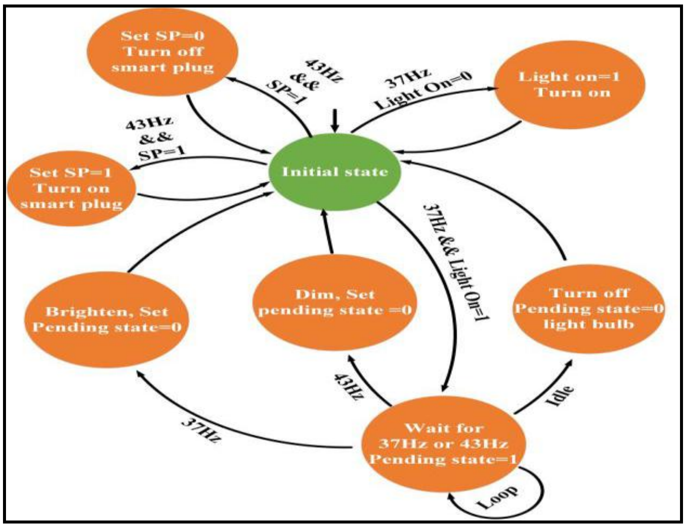


Fig -8: State diagram of home automation working model

3.3 Testing and Experimental Results

In this section, testing results of the BCI controlled home automation system with an auditory stimulus is presented. A smart light bulb was made to turn on, turn off, dim and brighten and a smart plug was made to turn on or off based on an auditory stimulus. Four individuals participated in testing. Prior to actual testing, these individuals had participated in few test trials using a preset detection threshold of 6.0 for SNR and a preset EEG peak threshold of 0.001µV in order to collect average SNR and a minimum EEG peak (minimum peak). Trials tended to yield a series of EEG detections originating from exposure to 37 Hz and 43 Hz tone. From here, an individual's unique SNR and minimum peak was extracted. SNR was found (per detection) according to differences between peak EEG values and background noise. The minimum peak is based off of the highest EEG peak from false detections that yielded small peak EEG values with respect to even smaller amounts of EEG noise. Upon the collection of SNR and a minimum peak, both SNR detection threshold and minimum peak threshold were changed to values found for each particular individual in an effort to limit false EEG detection. To further limit undesirable results, conditions in EEG processing were set to buffer detections by 15 seconds. After conduction of test trials, each subject underwent three trials to trigger 37 Hz or 43 Hz tones, depending on distance, where they were instructed to turn on, brighten, dim, turn off the smart bulb and turn on and turn off the smart plug via voice commands. Any trial yielding an incorrect voice command in compliance with the instructed command was deemed as inaccurate, and vice versa. Table I(A) and Table I(B) show the system response time obtained for each task of a trial and average accuracy of each task per individual in the smart bulb respectively.

Table -1(A): Peak detection time in seconds for smart bulb for four states

Table Head	*SNR value*	*No. of Trials*	*Turn ON(S)*	*Brighten by 25%(S)*	*Dim by 25%(S)*	*Turn OFF(S)*
Sub 1	6.57	Trial 1	22	15	15	25
		Trial 2	37	14	25	32
		Trial 3	18	19	27	12
Sub 2	7.06	Trial 1	20	19	15	17
		Trial 2	8	14	15	12
		Trial 3	4	16	17	29
Sub 3	6.27	Trial 1	7	12	24	40
		Trial 2	14	24	15	12
		Trial 3	22	20	22	26
Sub 4	5.71	Trial 1	14	14	11	16
		Trial 2	8	16	21	11
		Trial 3	31	10	19	13
Average Time (s)			17	16	17.6	20.4

Table -2(B): Average accuracy for smart plugged fan for two states

Table Head	*Turn ON*	*Brighten by 25%*	*Dim by 25%*	*Turn OFF*
Sub 1	66.7%	66.7%	100%	66.7%
Sub 2	100%	66.7%	66.7%	33.3%
Sub 3	100%	33.3%	33.3%	33.3%
Sub 4	100%	66.7%	66.7%	33.3%
Average	91.7%	58.3%	66.7%	50%

Overall in Table I(A), the average system response time for each task showed consistency. For the smart bulb, turn on response time had an average of 17 seconds. Similarly, average brighten response time and average dim response time took 16 seconds and 17.6 seconds respectively. Average system response time of the turn off state, however, yielded 20.4 seconds; this is slightly higher than the other three states. In terms of average accuracy from Table I(B), average accuracy of the turn on task was the highest at 91.66%. Average accuracy of the brighten, dim, and turn off tasks were calculated to be 58.33%, 66.70%, and 50% respectively.

Table -2(A): Peak Detection time in seconds for smart plugged fan for two states

Table Head	*SNR value*	*No. of Trials*	*Turn ON(S)*	*Turn OFF(S)*
Sub 1	6.57	Trial 1	5	24
		Trial 2	58	26
		Trial 3	5	45
Sub 2	7.06	Trial 1	17	9
		Trial 2	36	24
		Trial 3	70	37
Sub 3	6.27	Trial 1	22	20
		Trial 2	48	10
		Trial 3	52	12
Sub 4	5.71	Trial 1	39	20
		Trial 2	13	30
		Trial 3	8	13
Average Time (s)			31.09	22.5

Table -2(B): Average accuracy for smart plugged fan for two states

Table Head	*Turn ON*	*Turn OFF*
Sub 1	100%	100%
Sub 2	100%	100%
Sub 3	100%	66.7%
Sub 4	100%	100%
Average	100%	91.75%

Table II(A) and Table II(B) shows the system response time obtained for turn on and off tasks for each trial and average accuracy of each task per individual for a smart plugged fan. Average time for obtaining turn on and turn off commands are 31 and 22.5 seconds respectively. Smart plugged fan works cent percent with accuracy of 100% and 91% for turn on and turn off commands. In Table I(A) and Table II(A), there are occasional long detection times. Long detection times are a result of tight constraints on both the SNR threshold and minimum EEG peak threshold while attempting to eliminate false detections. Possible resolutions for long detection time include removing tight constraints and using machine learning to limit false detections. On the other hand, poor calibration resulted in false detections that lowered accuracy in the turn off smart bulb test (Table I (B)). A complex algorithm involving the need to idle in the turn off state (detection of no EEG signals for a time) displayed less accurate results as a consequence of poor calibration.

4. CONCLUSIONS

A BCI controlled home automation system, capable of activating various home devices such as lights, switches and ceiling fans, was presented. The control of devices is solely based on auditory signals received from the user. Two smart home (voice controlled) devices were used in system implementation: a smart bulb and a fan attached to a smart plug. Four subjects participated in the testing which involved three trials for each state of these two applications. Two factors were being measured, accuracy in the completion of the tasks and the response time of the system to complete each task. For the smart plug, tasks given were to turn it on and turn it off. The smart light bulb involved tasks to turn on, dim (by 25%), brighten (by 25%), and turn off the smart light bulb. The subjects who tested this system were able to turn on and turn off the smart fan with an accuracy of 100% and 91.75% respectively. Additionally, the task accuracy to turn on the bulb was 91.66%, dim was 66.70%, to brighten was 58.33% and to turn off was 50%. The experimental results reveal that the home automation devices can be operated efficiently and effectively using an individual's ASSR.

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