

# *Home Automation System using Brain Computer Interface Paradigm based on Auditory Selection Attention*

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**Abstract**—Brain Computer Interface is a technique through which a direct communication link can be established between a human brain and an external device using Electroencephalogram (EEG) signals. This technique implemented with a smart home system can be an effective remedy to help individuals suffering from speech and motion related disabilities. This paper presents a home automation system based on Auditory Steady State Response (ASSR) to mitigate speech and motion disabilities. The system comprises of an ultra-cortex headset, Arduino boards, speakers, personal computers with the processing IDE, SD card module, and proximity sensors. Two smart home (voice controlled) devices were used in system implementation: a smart bulb and a fan attached to a smart plug. Four subjects tested the devices where each subject performed three trials with a minute gap between each trial. Testing involved four states for the smart bulb, namely turn on, turn off, brighten by 25%, and dim by 25%. The smart plug was tested for its ON and OFF states. For each trial, system response time and accuracy were recorded. Average system response time for the smart bulb was found to be 17, 20.4, 16, 17.6 seconds with an accuracy of 92%, 50%, 59%, 67% for ON, OFF, brighten, and dim states respectively. Average system response time for the smart plug was found to be 31 and 22 seconds with an accuracy of 100% and 92% for its on and off states respectively.

**Keywords**—Auditory Steady State Response, Brain Computer Interface, Electroencephalogram, Integrated Development Environment, Home automation

## I. INTRODUCTION

The use of home automation devices has increased the quality of life for many individuals by providing them the ability to control home devices such as light bulbs, fans, garage doors, and thermostats. Unfortunately, a subsection of individuals are not able to take advantage of these advancements in technology. There are individuals who suffer from speech and motion related conditions such as Aphasia, Aphonia, Arthritis, Hemiplegia, Palsy, Paraplegia, as well as other motor neuron related diseases. Brain Computer Interface (BCI) has given the opportunity to 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 [1], 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.

Two methods of obtaining EEG signals for a BCI exist: invasive and non-invasive EEG. 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 [2]. 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.

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 artifact is presented in [3]. In this method, the authors use a visual stimulus to control a home automation system. A method to control a home automation system based on an attention level was presented in [4]; authors propose to control the home automation system by the amount of mental focus that the user places on a visual stimulus.

The authors of [5] propose to use Emotive EPOC to control a home automation system. Emotive EPOC uses three built-in suites to determine the various types of signal inputs based on emotions. An alternative approach in [6] created a smart home interface using Emotive EPOC. In [6], the user was able to control devices in the home by moving an emulated mouse in the GUI of the smart home's control panel using brain signals. The user clicks on the desired command by using facial expressions. Most of the research related to BCI based home automation systems designed and implemented their systems using visual stimuli, even though there are other methods to obtain EEG signals such as auditory stimulus and haptic muscle memory based technics.

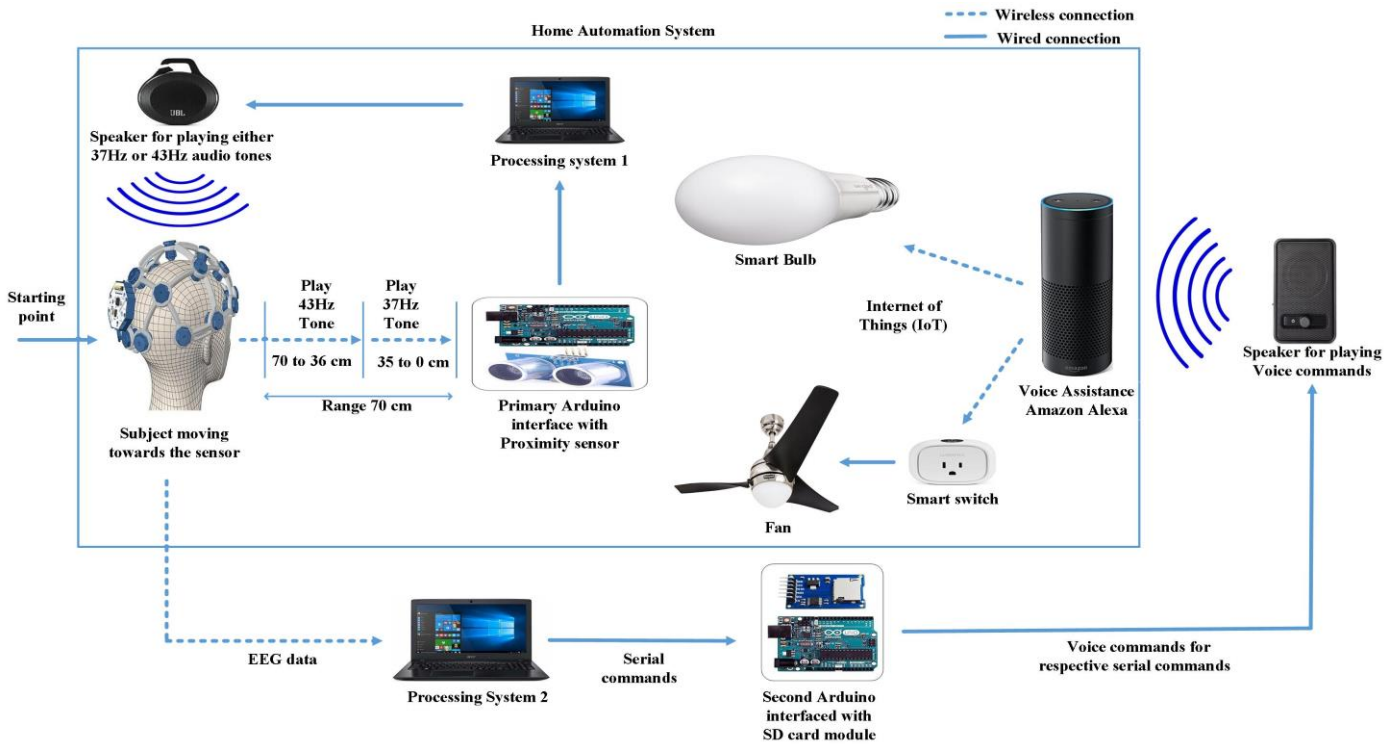


Fig. 1. Block diagram of home automation system based on auditory steady state response using OpenBCI interface

In this paper, a home automation system based on Auditory Steady State Response (ASSR) is presented. ASSR is based off obtaining the user's EEG signals from an auditory stimulus to operate a home automation system. Auditory stimuli based BCIs provide simplicity by utilizing the user's concentration on a steady tone in order to generate an EEG signal. While auditory stimuli results in lower accuracy than visual and haptic stimuli, auditory stimuli based BCIs, once completed, can help people unable to see (those unable to use visual stimuli based BCIs) or lack the ability to move muscles (those unable to use haptic stimuli based BCIs). The home automation system is capable of activating various home devices such as lights, switches and ceiling fans. The control of these devices is solely based on auditory signals received from the user. To test the system, an individual will perform a series of tasks in which the accuracy and response time of the system is measured.

## II. HARDWARE, DESIGN AND EXPERIMENTAL SETUP

The BCI based home automation system presented in this paper primarily 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 (shown in Fig. 1). 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

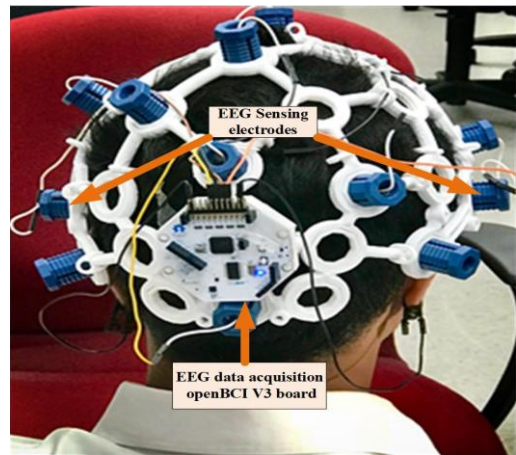


Fig. 2. Ultra-Cortex headset setup

Fig. 2 shows the Ultra-Cortex headset, with a version 3 OpenBCI data acquisition board attached, 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 a OpenBCI USB dongle. Electrodes of the headset are positioned on the scalp according to international 10–20 measurement standards [7] to acquire proper EEG signals.

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. 3. 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.

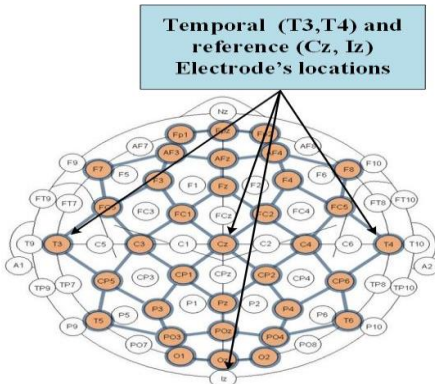


Fig. 3. Electrode positions [8]

## B. Home Automation System Setup

The set up as shown in Fig. 1 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 [9] 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 predetermined 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 [9]. 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.

### 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. [10]. These devices interact with Alexa in a common network using a Wi-fi router. Configuration is set up using the Alexa application and TP-link 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. 4 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. 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-to-noise 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  $\mu V$ , with respect to the average noise, also measured in  $\mu V$ , 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  $\mu V$  with a lower average noise level of .00001  $\mu V$  results in an SNR of 50, making for false detection). Minimum EEG peak threshold is set between .001 to .003  $\mu V$  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.

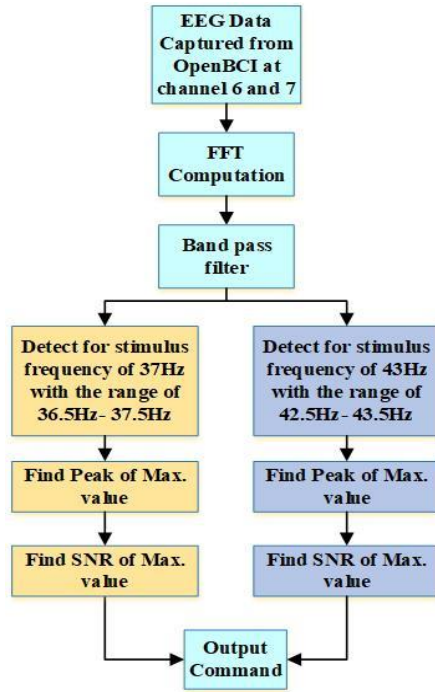


Fig. 4. Flow chart of EEG processing

### III. METHODOLOGY

Possible states for the light bulb and smart plug are shown in Fig. 7. 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. 7) provide distinguishable difference in frequency and viability as a means of detection compared to other tones [9]. Frequency response of EEG signal data, measured in in  $\mu\text{V}$ , at 37 Hz and 43 Hz are shown in Fig 6(a) and Fig 6(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. 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. 7). Following this procedure, the lightbulb will turn on (entering the "turn on" state of Fig. 7).

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. 7) 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

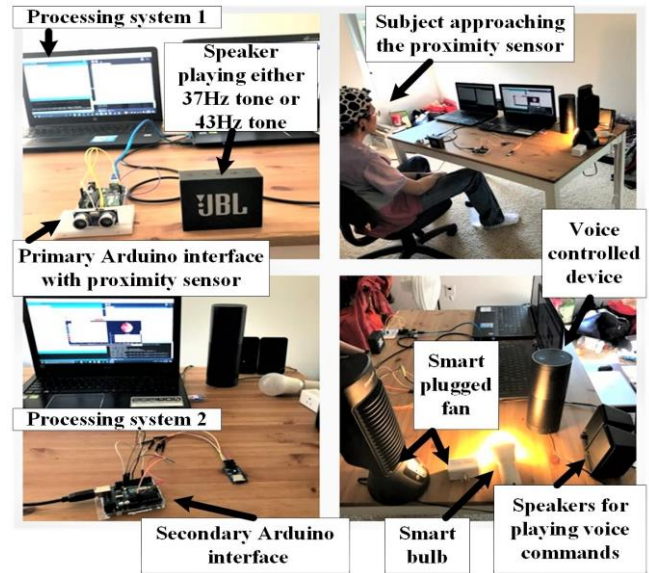
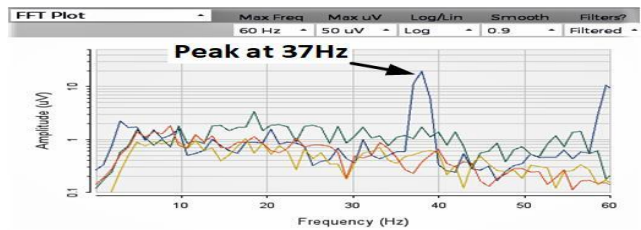
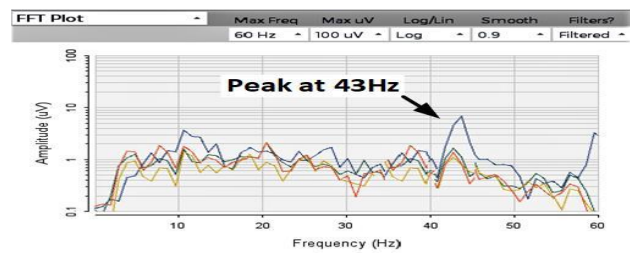


Fig. 5. Experimental set up and its working demo



(a). 37 Hz Peak detection



(b). 43 Hz Peak detection

Fig. 6. Frequency response of EEG signal data

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.

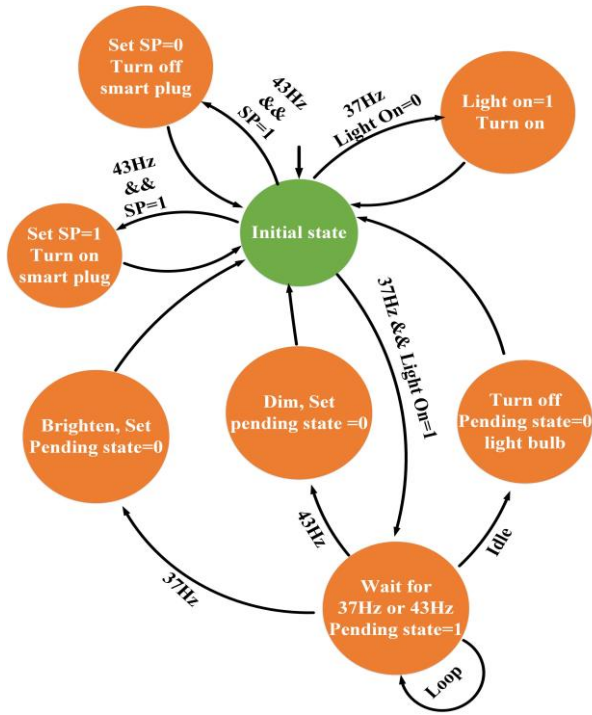


Fig. 7. State diagram flow of home automation working model

#### IV. 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  $0.001\mu V$  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 I (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 I (B) AVERAGE ACCURACY FOR EACH STATE OF SMART BULB FOR FOUR 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 II (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 II (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%
<b>Average</b>	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.

## V. CONCLUSION

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.

## VI. FUTURE WORK

Advancements in technology are producing effective smart devices and applications that can be controlled by a home automation system. The proposed system can be expanded to be used to control the growing number of home devices and applications with a focus on individuals with disabilities. The proposed system used two different auditory tones to control two home devices. It can be expanded to include a wider range of auditory tones which will allow for

control over a greater number of home devices such as garage door openers, automatic door locks, thermostats, and security systems as well as many smart devices with emerging technology. The second factor that can be improved is the accuracy. Improving the SNR and peak threshold base for a given individual will result in an improvement in the accuracy of the system. The proposed system presented in this paper is intended for use on people with disabilities but can be expanded to a wider user base, to individuals who may not have any disabilities. Additionally, a real system could use a single Arduino and computer with the processing ide can be used to increase accuracy. Accuracy would be increased by communicating additional information, such as the type of tone playing, in order to limit false detections.

## ACKNOWLEDGEMENT

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## REFERENCES

- [1] Anirudh Vallabhaneni et al., "Brain—Computer Interface", 1st ed.: Springer US, 2005, pp 85-121
- [2] Aashit K. Shah, Sandeep Mittal, "Invasive electroencephalography monitoring: Indications and presurgical planning", *Ann Indian Acad Neurol.* 2014 Mar; 17(Suppl 1): S89–S94.
- [3] Goel, K., Vohra, R. and Baths, V. (2014). Home Automation Using SSVEP & Eye-Blink Detection Based Brain-Computer Interface. [PDF] San Diego, CA, USA: IEEE International Conference on Systems, Man, and Cybernetics, pp.4035-4036.
- [4] Ghodake, A. (2016). Brain Controlled Home Automation System. [PDF] San Diego, CA, USA: 2016 10th International Conference on Intelligent Systems and Control (ISCO), pp.1-4.
- [5] Lee, W., Nisar, H., Malik, A. and Yeap, K. (2013). A brain computer interface for smart home control. [PDF] San Diego, CA, USA: IEEE Conference Publications, pp.35-36.
- [6] Alrajhi, W., Alalool, D. and Albarqawi, A. (2017). Smart Home: Toward Daily Use of BCI-Based Systems. [PDF] San Diego, CA, USA: IEEE Conference Publications, pp.1-5.
- [7] S. Haggag, S. Mohamed, A. Bhatti, H. Haggag and S. Nahavandi, "Noise level classification for EEG using Hidden Markov Models," *2015 10th System of Systems Engineering Conference (SoSE)*, San Antonio, TX, 2015, pp. 439-444.
- [8] Chip Audette, "Controlling a Hexbug with my Brain Waves", June 8, 2014 [Online Blog] Available at : <http://eeghacker.blogspot.com/2014/06/controlling-hex-bug-with-mybrain-waves.html>
- [9] Kim, D., Cho, J., Hwang, H., Lim, J. and Im, C. (2011). A vision-free brain-computer interface (BCI) paradigm based on auditory selective attention. In: *33rd Annual International Conference of the IEEE EBMS*. [PDF] Boston: IEEE Conference Publications, pp.3685-3687.
- [10] Hwaiyu Geng, "THE BRAIN—COMPUTER INTERFACE IN THE INTERNET OF THINGS," in *Internet of Things and Data Analytics Handbook*, 1, Wiley Telecom, 2017, pp.816