An Affordable Brain-Computer Interface for Electrical Energy Applications

Sheriff Sadiqbatcha, Saeed Jafarzadeh
Computer and Electrical Engineering
California State University Bakersfield
Bakersfield, CA
is-green@cs.csub.edu

Abstract **—This paper discusses the implementation of brain-computer interfacing technology in the field of electrical energy and power systems. An electroencephalograph headset is utilized to read relative attention levels of the user and a system is developed which utilizes the attention level signal as a command to trigger an electric-device.A low cost and user friendly commercial solution is considered to target a wide span of applications. Some aspects of signal analysis are also implemented and discussed in the given context.**

Keywords—**Brain-computer Interface, Electroencephalograph, Attention Level, Signal Processing.**

I. Introduction

All executive and motor functions of the human body, whether voluntary or involuntary, have one common root. Mankind has always been fascinated by the intricacy of the human brain but has never been able to unlock its secrets.After all, tracing through a network of 100 billion neurons is an overwhelming task by any-ones standards. Over the years as new technologies emerge, doors have been opened in the path to better understanding the brain and its functional structure. Thus far solely been reserved for the medical field, recent advancements in safety and accessibility has made possible such technologies to be utilized in other applications. Electroencephalography (EEG) is one suchtechnology, which isused to record electric potentials generated by neurons in the brain throughexternal placement of electrodes on the scalp [1]. Since electrode placement is peripheral and it solely functions as a medium of gathering data without interfering with any of the brains functionalities, EEG can be utilized without the supervision of a medical professional. This allows it to be implementedin a wide variety of applications without any concerns of health risks to the targeted user. Although EEG has a higher temporal resolution than functional Magnetic Resonance Imagining, it significantly lacks inits ability to deliver comparable spatial resolution [1].Moreover, possibilities of noise and inconsistencies in the signal caused by sources not associated with the brain has to be considered and addressed in-order for the signal to be viable [2].Offering such opportunities and challenges, EEG signals, provide reliable and yet costly interface for human-machine interactions.

Brain-computer interface technology is a rapidly growing field of research. Recent technological advancements enabled introduction of brain-computer interfacing to a variety of applications [3], [4]. A number of research studies reported various ways in controlling robotic platforms signifies the interest in this field [5]-[8]. However, the use of this technology in the field of electrical energy and power systems is not investigated. This research study focuses on the applications of brain-computer interface technology in electrical energy-related industries. To target a wide span of applications, we considered an affordable commercial solution for brain-computer interfacing.

The paper is organized as follows. In Section II, we present a general description of the paper’s background. The hardware and software designs are explained in detail in Section III. We demonstrate our experimental developmentprocess in Section IV. Conclusions and suggestions for future work are given in Section V.

II. Background

Electroencephalography is the measurement of electrical activity generated by neurons in the brain. A composite reading of the electrical signals generated by neurons in a given section of the brain is non-invasively measured by placing electrodes on the scalp. Strategic placement of electrodes in different areas of the scalp and analysis of the signals yield a variety of information that relates to the current mental and emotional state of the brain. Ishihara and Yoshii found a distinct theta activity of EEG over frontal midline area during mental tasks, which is called Fmϴ [9]. It has been found that some electrical activity in the Fmϴarea can be linked to a state of mental concentration [10].

The EEG signal obtained from the frontal lobe, when transformed from time domain to frequency domain using Fast Fourier Transform, provide us with clearly distinguishable distributions of frequencies linked to different mental and emotional states [11]. The EEG signal patterns in time domain and frequency bands related to different mental states are shown in Fig. 1 and Table I respectively.

Analysis of the data gathered from the FmΘ area in frequency domain enables us to measure one's relative level of alertness at any given time. Using this principle, a subject's attention level can be monitored in real time and used as a trigger or command to execute a predetermined task.

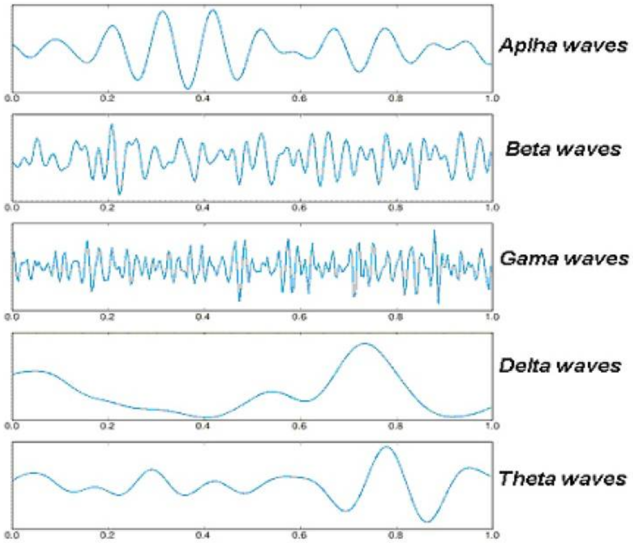

Fig. 1 - EEG signal patterns [11].

TABLE I. EEG FREQUENCY BANDS AND RELATED MENTAL STATES [11]

TYPE	FREQUENCY	MENTAL STATES
Delta	0.1Hz to 3Hz	Deep, dreamless sleep, non-Rem sleep, unconscious.
Theta	4Hz to 7Hz	Intuitive, creative, recall, fantasy, imaginary, dream.
Alpha	8Hz to 12Hz	Relaxed, but not drowsy, tranquil, conscious.
Low Beta	12Hz to 15Hz	Formerly SMR, relaxed yet focused, integrated.
Midrange Beta	16Hz to 20Hz	Thinking, aware of self & surroundings.
High Beta	21Hz to 30Hz	Alertness, agitation.
Gamma	30Hz to 100Hz	Motor functions, high mental activity.

One application of this technology, which is the main focus of this paper's study, is its use in mind-controlled electric devices.As previously mentioned, any extended level of focused attention towards a specific object of interest can be traced using this method, therefore can be used as a command to execute the objects functionality i.e. turn a device on or off. This allows the system to be adapted as a control for certain electric devices, thereby can possibly grant disabled individuals further control of electronics in their home.

Another application of such technology can be realized in high risk industry. EEG sensors can be incorporated in the helmets of workers so that their attention values can be logged during their work day. The readings can be wirelessly transmitted to a central system allowing a supervisor tomonitor the status of each individual worker in real time. Low attention level for an extended period of time can be detected and used to trigger a buzzer or notify the supervisor so that immediate actions can be taken to remove the worker from the high risk environment, thus tremendously reducing the chances of accidents.

III. HARDWARE AND SOFTWARE DESIGN

In this system the Mindwave Mobile headset by NeuroSky, Inc. is utilized to read the EEG signals. Not only is this device affordable in comparison to other consumer EEG sensors in the market, it is also very compact. Its wireless interface makes it ideal for wearable electronic applications. NeuroSky's eSence algorithm processes the EEG signals onboard and wirelessly transmits the calculated attention and meditation values through Bluetooth to a master device at the rate of 1Hz.

A HC-05 Bluetooth module, programmed with the MAC address and password of the Mindwave headset, acts as the master device that automatically pairs with the headset once both devices are powered on. The data received by the HC-05 module is then transmitted to an Arduino microcontroller.

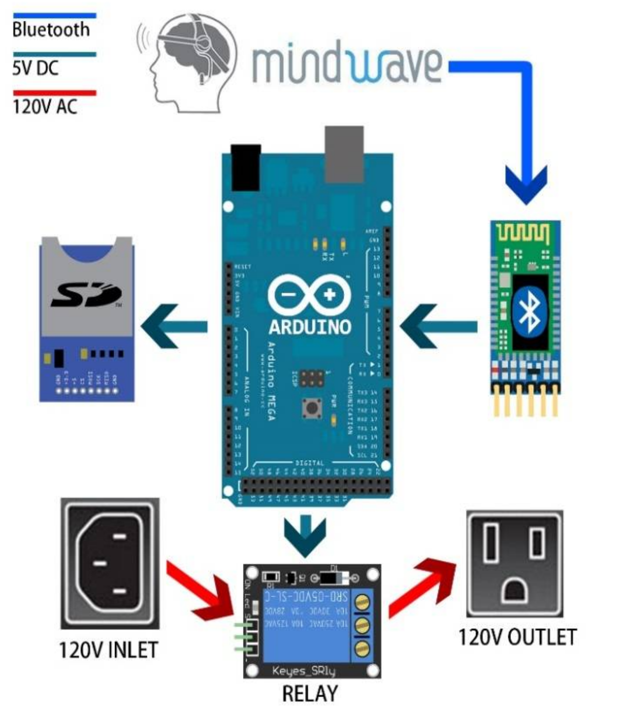

Fig. 2 - Mindwave interface with HC-05 module and Arduino Mega 2650. Data logging using SD module. Communication from headset to HC-05 made thru Bluetooth v2.1 Class 2. Communication from HC-05 module to Arduino Mega made thru UART (Serial) 57,600 Baud. Communication from Arduino Mega to SD module made thru Serial Peripheral Interface (SPI). 5V digital connection from Arduino to relay. Relay used to close a 120V circuit when triggered.

The Arduino is an open-source microcontroller board, incorporating an ARM processor, which can be configured by writing software using its dedicated development environment. In this system, the Arduino microcontroller is used to gather and analyze the data from the headset to be used in real-time or stored for future analysis. A Secure Digital Card (SD) module is added to the system for data storage.

A relay is used, in conjunction with an inlet and an outlet, allowing an AC circuit to be controlled with a digital signal from the Arduino. The circuit is designed such that when the Arduino detects the command from the user, it sends a digital high signal to the relay, which in turn closes the AC circuit, thus powering on any electric device that may be connected to it.The general schematic of the system is shown in Fig. 2.

IV. EXPERIMENTALDEVELOPMENT

The Mindwave headset does onboard calculation of the EEG data and outputs a relative attention value in a scale of 0 to 100. In order to fully understand the sensitivity of the device, an initial set of data had to be collected where a test subject was asked to performvarious activities involving different levels of concentration. The activities were reading, relaxing, staring, talking, and watching a video. Eachactivity was performed for duration of four minutes while the calculated attention values were logged. Mean and standard deviation were calculated from the recorded data in order to better understand the correlation of the performed activity and the recorded attention values. Table IIshows the calculated mean and standard deviation values for each of the activities.

TABLE II. MEAN AND STANDARD DEVIATION OF THE ATTENTION LEVEL SIGNAL

ACTIVITY	***MEAN***	***STANDARD DEVIATION***
Reading	53.54	17.31
Relaxing	39.55	15.99
Staring	67.22	18.23
Talking	51.49	18.29
Watching a video	55.46	15.91

Attention scale 0 - 100

As discussed earlier, this system calls for a specific activity performed by the user, which can be used as a command to initiate a predetermined task. This activity has to be clearly distinguishable from all the others inorder to avoid false triggers.The data shows that the attention level of the user while staring is significantly higher than the rest of the activities. Therefore, staring at the object of interest was selected as the controlling command for the system. Fig. 3 shows the characteristics of the attention level signal while staring.

Although the average attention values while staring are significantly higher than the rest, it cannot be implemented directly as the command since the raw signal proves to have a significant noise component. A smooth signal curvethat stays within a certain amplitude while the user is performing the selected activity is needed, so that it can be easily detected by the system. In order to obtain a usable signal, the following moving average (MA) filter was implemented.

$$y_i = \frac{1}{M}\sum_{j=0}^{M-1} x_{i-j} \tag{1}$$

In this filter the variable$M$ is the size of the subset windows that is used to calculate the average, x_i is the current unfiltered attention value, the summation of x_{i-j} is the sum of the previous M number of data points and y_i is the resulting value from the filter.

The moving average is the most common filter in Digital Signal Processing. In spite of its simplicity, the moving average filter is optimal for a common task: reducing random noise while retaining a sharp step response [12]. This makes it a common time-domain filtering approach in signal processing.

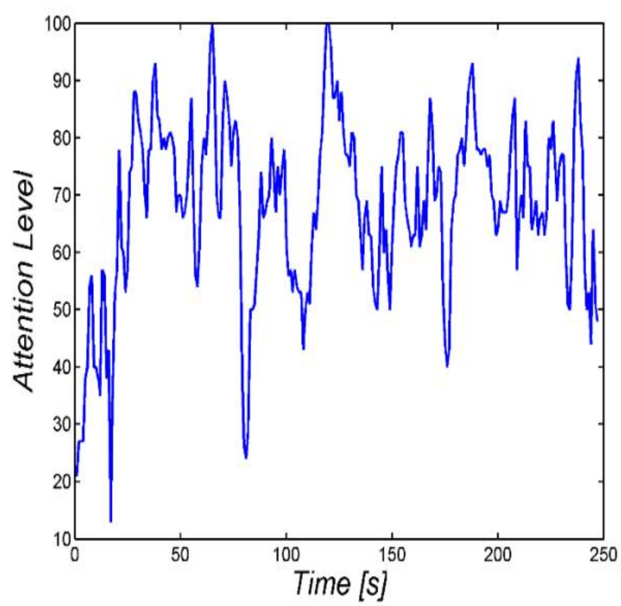

Fig. 3 - Characteristics of the attention levl signal while staring shown in time domain.

The MA filter works by taking the average of all the data points in a given subset window in order to minimize the effects of fluctuations in the signal, therefore more points in average produces a smoother signal curve. For this instance, the number of data points used in the filterwas incrementally increased until a desirable signal was obtained. After multiple tests it was found that a window size of 20 data points was required in order to obtain a signal that can be used for the purposes of the system. Fig. 4 shows the attention level signal after the MA filter is applied.

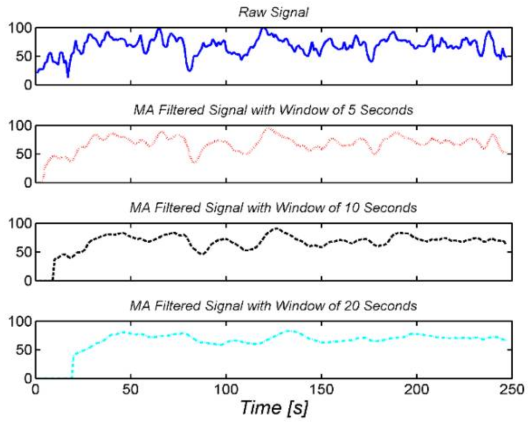

Fig. 4 - Time domain representation of the raw attention level signal in comparison with the resulting filtered signal from the MA filter using different window lengths.

Although this filter was sufficient for post analysis of the data, considering the eSence system's limitation of processing the signals at merely 1Hz, and the fact that in order for the signal to be usable, the filter had to have a window size of at least 20 points, it caused a tremendous delay in correlation of the output with the real time EEG readings.To address this issue the signal had to be further analyzed so that a more practical filter can be created to reduce the delay.To successfully avoid the noise, we need to identify its frequency domain characteristics. Therefore, assuming that the desired signal is a constant value, we subtracted sample mean from collected data to obtain an approximation of the noise. Then, the resulting signal was converted to frequency domain using Fast Fourier Transform(FFT). The magnitude of the fourier transform of the noise is shown in Fig. 5.

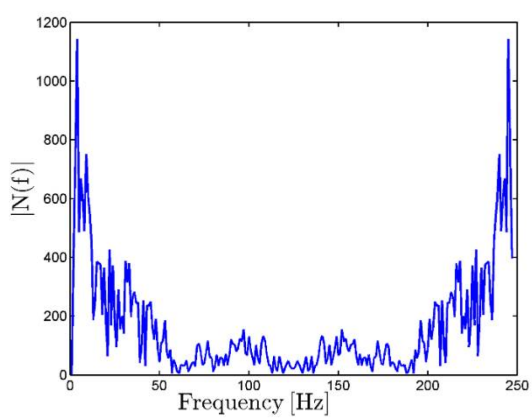

Fig. 5 - Frequency domain representation of the raw attention level signal.

Further studies of the signal in frequency domain concluded that the noise was most dominant in the higher frequencies, thus a low-pass filter was needed to remove the noise from the desired signal.

In order to simplify the filtering process, two of the most common and elementary low-pass filters were selected. Namely a Finite Impulse Response (FIR) filter and an Infinite Impulse Response (IIR) filter were implemented and tested on the system. These filters are used to discriminate a frequency or a band of frequencies from a given signal which is normally a mixture of both desired and undesired signals.In case of a FIR filter, the response due to an impulse input will decay within a finite time, whilein the IIR filter the impulse response never dies out. It theoretically extends to infinity [13].

The equation for the FIR filter that was used is gives as:

$$y_i = \alpha x_i + (1-\alpha) y_{i-1} \tag{2}$$

In this equation the variable α is the multiplying coefficient used to disregard the undesired frequecies from the given signal, x_i is the current unfiltered attention value, y_{i-1} is the filtered value from the previous itteration and y_i is the current resulting filtered value.

The IIR filter that was used is as follows.

$$y_i = \alpha \frac{x_i + x_{i-1}}{2} + (1-\alpha) y_{i-1} \tag{3}$$

The IIR filter is fundamentally similar to FIR but incorporates some aspects of the MA filter. Whereas the FIR filter only uses the current unfiltered attention value in the computation, the IIR takes into consideration the average of the previous two attention values.

After extensive testing with these filters, it was found that a α value of .2 yielded the most usable results in terms of decreasing the amount of fluctuations in the signal and the delay caused by the filter. Fig. 6 shows the comparison of the raw attention level signal and filtered signal using FIR and IIR respectively.

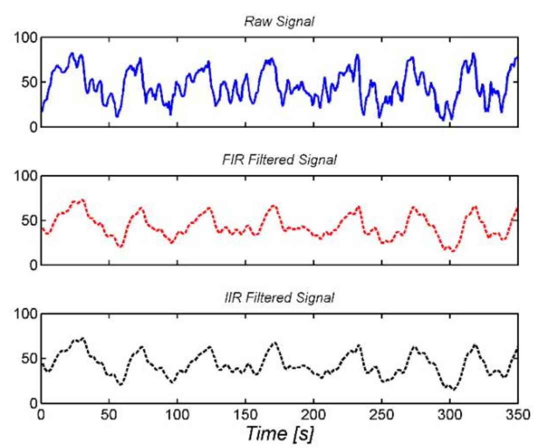

Fig. 6 - Time domain representation of the raw attention level signal, and the resulting signal from the FIR and IIR filteres. The peaks indicate the instances when the user stares at the object of interest.

The filtered signals were still slightly irregular and there was still some delay in the correlation with the raw readings, but none the less it was a tremendous improvement from the previous filter as it provided a useable output with a much more acceptable delay.

Repeated tests showed that in average the FIR filter caused a delay of 10 to 15 seconds for the signal to steadily rise to the desired threshold and trigger the command. Whereas the average delay using the IIR filter was between 6 to 12 seconds. Therefore, the FIR filter was disregarded and the IIR was selected to be used on the system.

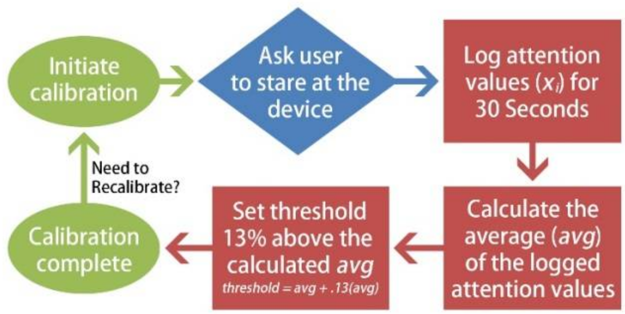

Fig. 7 - Illustration of the sequential process executed during the calibration.

At this point the filtered attention level signal is stable enough to be used as a command. As previously mentioned, the system is designed such that in order for the command to be executed the user simply has to stare at the object of interest, which in-turn shows a clear response on the attention level signal. When the attention level reaches a certain threshold it is taken as a queue to execute the given function, i.e. turn alight bulb on or off.

Finding that threshold, however, proved to be a challenge on its own. Tests conducted on multiple subjects showed that a hard coded threshold is not practical since the attention reading from one subject to another or even for the same subject at different occasions, differed significantly. Therefore, whilst a certain threshold works for one, it might be too low for another that it triggers a false command or, on the other hand, too high to reach despite extensive effort.

Fig. 8 - The developed system used as a control for a desk lamp.

To address this issue the system had to be made adaptive such that it learns the characteristics of the user's attention signal at that given time and generates a threshold that is only reached while the user performs the controlling command.A push button is added to the system, when the button is pressed the system executes calibration mode. Calibration mode is set to a period of 30 seconds where it stores the base readings of the attention values. The average of the data collected over the calibration periodis calculated and the threshold is set at a value 13% above the calculated average. During the calibration period the subjects are asked to perform the controlling command, which in this case is staring at the device. This allows the system to log their attention values while they perform the task and set the threshold based on the readings. The calibration process ensures that the set threshold is tailored to the current user, and is surely reached when the user performs the controlling command. The calibration procedure is illustrated in Fig 7.

Although we now had a working system that can be successfully used as a control to switch a device on or off, the delay proved to be too cumbersome since the user had to stare at the device for an average of 6 to 12 seconds to activate the command.In order to reduce the delay, an algorithm had to be developed such that the user's interest in triggering the devicecan be predicted earlier on before the filtered attention signal even reaches the set threshold. After careful calculations it was found that if the current filtered attention value is above 70% of the set threshold and it increases by 12% of the threshold in a period of 2 seconds, it can be confirmed that the user is staring at the device. Implementation of this algorithm on this system allows the trigger to be activated not only when the signal reaches the threshold, but also when the given conditions are met.This new condition tremendously reduces the delay,as tests prove that in average the command can now be triggeredwithin 5 seconds of staring at the device.

The combination of the adaptive feature and the algorithm used to trigger the command, makes this system a viable and user friendly switch that can be used to trigger any simple electric device. One possible application of this system is illustrated in Fig. 8.

V. CONCLUSION

Whilst the developed system exemplifies the concept of accessible mind-controlled electric devices implemented in an everyday home setting, in its current state it is infeasible as it can only be used to control one device at a time. However, use of a more robust EEG headset that incorporates multiple sensors will make possible the ability to control a number of these systems simultaneously. One such headset is the Emotive EPOC+, which incorporates 14 EEG channels and 2 references. Whilst the Mindwave headset used in this system only calculates relative attention level of the user, the EPOChas the ability to detect EEG signals specific to a thought. This allows for a network of these systems linked to the same EEG headset, where each system is trigged by a different controlling command. For instance, one can be connected to a lamp and another to a fan, therefore in-order to turn on the fan the user simply has to think “fan”, and vice versa.When used accordingly, this system could possibly be utilized to grant a disabled individual further control of electric devices in their home.

Whether it’s in a home or an industrial setting, this paper demonstrates the ever expanding realm of brain-computer interfacing technology. Considered at one point solely as a tool of diagnosis in the medical field, it is now realized that such technology can be implemented in a wide variety of scenarios. The proposed system is just one of the infinitely many applications of such technology in the field of electrical energy and power systems.

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Sheriff Sadiqbatcha is a senior student in computer engineering program at CSUB. Sheriff’s research is currently focused on using fuzzy logic for sparse matrices with application to power system state estimation. Sheriff is the current President of the Computer Science & Engineering club of CSUB for the 2015 academic year. He is also an active member of the IEEE Student Branch of Bakersfield. Outside of academia Sheriff is a professional Graphic Designer and a web developer.

Dr. Saeed Jafarzadeh is an Assistant Professor at CSUB since 2012. He received a Ph.D. at the University of Nevada, Reno. His research interests include power systems, smart grid, renewable energy systems, energy markets, and energy conversion. His current research focus is on interdisciplinary aspects of energy industry such as stability analysis of energy markets, forecasting renewable energy resources, quantification of smart grid policies, optimization of energy conversion systems, and power systems dynamic state estimation. He has more than 30 publications in prestigious IEEE journals and international conferences. He provides leadership in directing the Power Systems Laboratory and IS-GREENto serve the students in the Electrical Engineering program(www.cs.csub.edu/~is-green).