EEG-Based BCI for Household IoT Control

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Abstract

Objective. Brain-computer interface (BCI) paradigms have existed for decades to improve communication and technological control. Electroencephalography (EEG) represents one of the most common non-invasive approaches toward recording brain signals in human participants [1]. Many features within EEG signal are used to model BCI including five major types of brain wave frequency bands, autoregressive parameters, and power spectral density values [2]. Processing EEG to produce a desired output demands signal filtration, feature extraction and classification. *Approach*. Using the Emotiv EPOC+ headset, electrodes placed on the scalp record passive mental activity at centimeter resolution [3]. The EPOC+ represents a low-cost alternative to medical-grade hardware, which may allow the development of this platform to be more accessible to end-users. Filtration and classification methods are applied to distinguish signal frequencies of interest. The recorded EEG signal is used to demonstrate potential for passive control a simple household appliance such as a light fixture. To this end, a participant's passive EEG is recorded during a series of tasks in varying light settings. In addition to technical challenges, there are practical considerations to overcome, such as variability and subject fatigue. Preliminary results suggest a measurable distinction in mental state between tasks. *Significance*. Following this line of inquiry, a platform for interfacing with the increasingly ubiquitous internet of things (IoT) may be developed in the future. The potential applications of BCI are myriad and promise to better living conditions by enhancing and supplementing central nervous system output. EEG-based signaling may provide means to greater autonomy and technological accessibility for disabled people and patients with neurological deficits.

1. Introduction

The means of recording neurophysiological signals via electroencephalograph (EEG) has existed for over one hundred years [4]. The scalp EEG has allowed researchers to non-invasively study and monitor the state of the brain using electrodes distributed over regions of interest. A typical EEG signal consists of many features and often appears as an irregular, dynamic wave pattern. Traditional power spectral analysis separates EEG signal into major frequency bands: delta, theta, alpha, beta, and gamma. A large and ever-growing body of research supports EEG signal patterns as a viable brain-computer interface (BCI) [5]. High temporal resolution in EEG measurement offers the potential for close to real-time control of an actuator. EEG has been shown to be increasingly portable, inexpensive, and easy to use.

The Internet of Things (IoT) represents the integration of various technologies with different capabilities [6]. Still in the nascent stage of development, IoT enables personalized services toward a user's interaction with a device. Several IoT domains of active development include health, remote monitoring, and process automation. One of the major challenges of IoT development is the integration of diverse technologies and standards. In the future, it is possible that bio-metric devices will be IoT-capable to enable health monitoring and smart home control.

Existing EEG research has examined self-reported changes in fatigue, frustration, and attention with good accuracy [7]. Additionally, an active area of EEG research is in control of appliances and prosthetics. However, little research has been done to examine the effects of light exposure on EEG signal outside of sleep-deprivation studies. Light exposure represents a simple variable for which to identify distinguishing EEG signal patterns. A difference in passive mental state may one day prompt useful output by a smart-home algorithm.

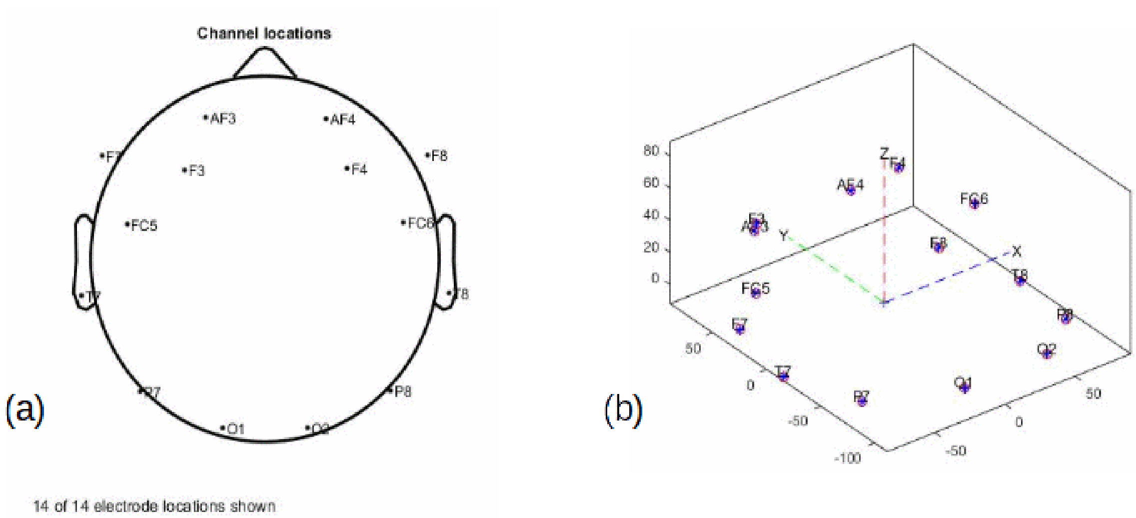

Figure 1. (a) The locations of each EEG channel as overlaid over the head in two dimensions and (b) in three dimensions. Channel location plots are constructed in MATLAB from data collected by the EPOC+. EEGLAB software reads channel locations from Cartesian coordinates provided from the device.

2. Materials and Methods

2.1 Experimental Protocol

In this study, the Emotiv EPOC+ is used to demonstrate the feasibility of a passive-EEG based BCI. The Emotiv (Emotiv, San Francisco, CA) platform offers EEG recording hardware and software. The EPOC+ headset utilizes 14 channels with electrode placement based on the international 10/20 system. The device transmits recorded EEG signal via Bluetooth to a PC for processing.

This study will attempt to demonstrate a difference in passive mental states between reading in high and low ambient light settings. Specifically, EEG will be recorded while the user reads text in variable light settings to determine differences in mental state. One participant was recruited for this study. The participant completed a 1-hour session in a single day. To minimize the effect of movement on the recorded EEG signals, the participant was instructed to remain still during recording. The participant maintained an upright, seated position for the duration of each recording session.Additionally, the participant inserted ear plugs to minimize distraction and effect from auditory response potentials. Care was taken to minimize distractions and noises that might change the participant's attention.

2.2 Data Collection

EEG data is collected using the EPOC+ headset setup per manufacturer's instructions and connected to a PC using EmotivPRO software. Signals were acquired from 14 electrodes placed at the following positions described in Figure 1. The sampling rate is 128 Hz. All recordings were made to be one minute in length and preceded by thirty seconds of recorded activity. As a comparison, the participant's EEG signal under a blindfold was recorded. Then ceiling lights and a reading light were turned on for the next session of recordings in which the participant read text from out of a book. After this, the lights were turned off and a single candle was then used by the participant to read from five feet away. The participant read from a book without repeating passages to emulate a real-world use case. Five sessions per activity per participant were recorded. Bluetooth connection was maintained within a five foot distance between device and dongle. Due to low quality of recording, the least noisy recordings from each task trial were kept for processing.

2.3 Data Processing

After recording is completed in EmotivPRO, the data is exported to the EDF file format. The MATLAB (MathWorks, Natick, MA) toolbox, EEGLAB [8], is chosen for data analysis. Pre-processing the EEG data before analysis is necessary. Imported as EEGLAB datasets, the signal is first re-referenced to the two reference channels. The EPOC+ comes standard with a fifth-order SINC filter to low-pass filter signals below 50 Hz. In EEGLAB, a 0.5 Hz high-pass filter is applied. An automated noise-removal tool, CleanLine, is applied to the signal. Bad channels and large artifacts such as scalp and jaw muscle movements are stripped from the signal using statistical methods (Figure 2). With the processed data, the power spectral density, channel activity and component analysis can be plotted to identify frequencies and channels of interest associated with each task.

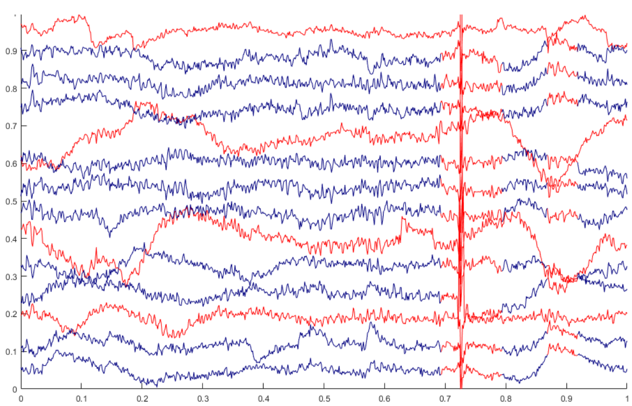

Figure 2. A screen capture from EEGLAB visualizing the identification of bad channels and artifacts. Bad channels are identified using statistical methods and removed from analysis. Bad channels usually result from poor connectivity. A large artifact, most likely a scalp muscle movement can be seen in this frame after 0.7 sec.

3. Results

3.1 Spectral Density

From the spectral density data shown in figures, some patterns become apparent. During the blindfolded session, the participant exhibited a spike in alpha wave frequency rhythms (8 Hz). This is largely consisted with similar data in literature SOURCE NEEDED. In the high ambient light trial, there is a much smaller alpha rhythm spike accompanied by a blank. The last trial, the low light trial, showed a similar pattern to the high light spectral density, albeit with lower alpha rhythm detection and a spike in beta rhythms.

3.2 Independent Component Analysis (ICA)

Using EEGLAB functions, an independent component analysis was performed. Also known as blind source separation, this method maximizes the degree of statistical independence between outputs. The ICA for each trial can be seen in Figure 3.

3.3 Limitations

There are several limitations in using the EPOC+ model. Of note, the working distance of the platform between the user and the Bluetooth dongle was quite short, around five feet. The wireless characteristic of the model severely limits the range of tasks that can be meaningfully be tested on the Emotiv platform as well as contributed to bad channel data. It has been shown that consumer grade devices, such as the EPOC, exhibit high variability of data [9]. The impedance of the saline solution changes over time as the sensors dry due to user body heat. Additionally, the hair of the user is an obstacle to signal quality. Participant noted discomfort after the session. Additionally, there were limitations to this study including, but not limited to, the small number of participants and recordings.

4. Discussion

Studies have shown relationship between EEG power spectrum and task performance [10]. One group suggests that posterior alpha band activity is a critical indicator of attention and frustration in the user [7].The data gathered from this study can be applied to the Neuroberry platform, a CAC-based framework primarily developed for gaming [11]. The Neuroberry group achieved success in using the EPOC model as a remote control. One group has shown success combining the Emotiv EEG headset with a mounted camera, which prompts interface when the user looks at a device [12]. As the camera recognizes a device, the user performs a trained action for the EEG sensor interpret. Such gestures would comprise a motor-imagery based BCI through kinesthetic imagination of the limbs [13].

As EEG data sets continue to grow and become available to researchers, machine learning algorithms will be able to identify previously unseen patterns within the

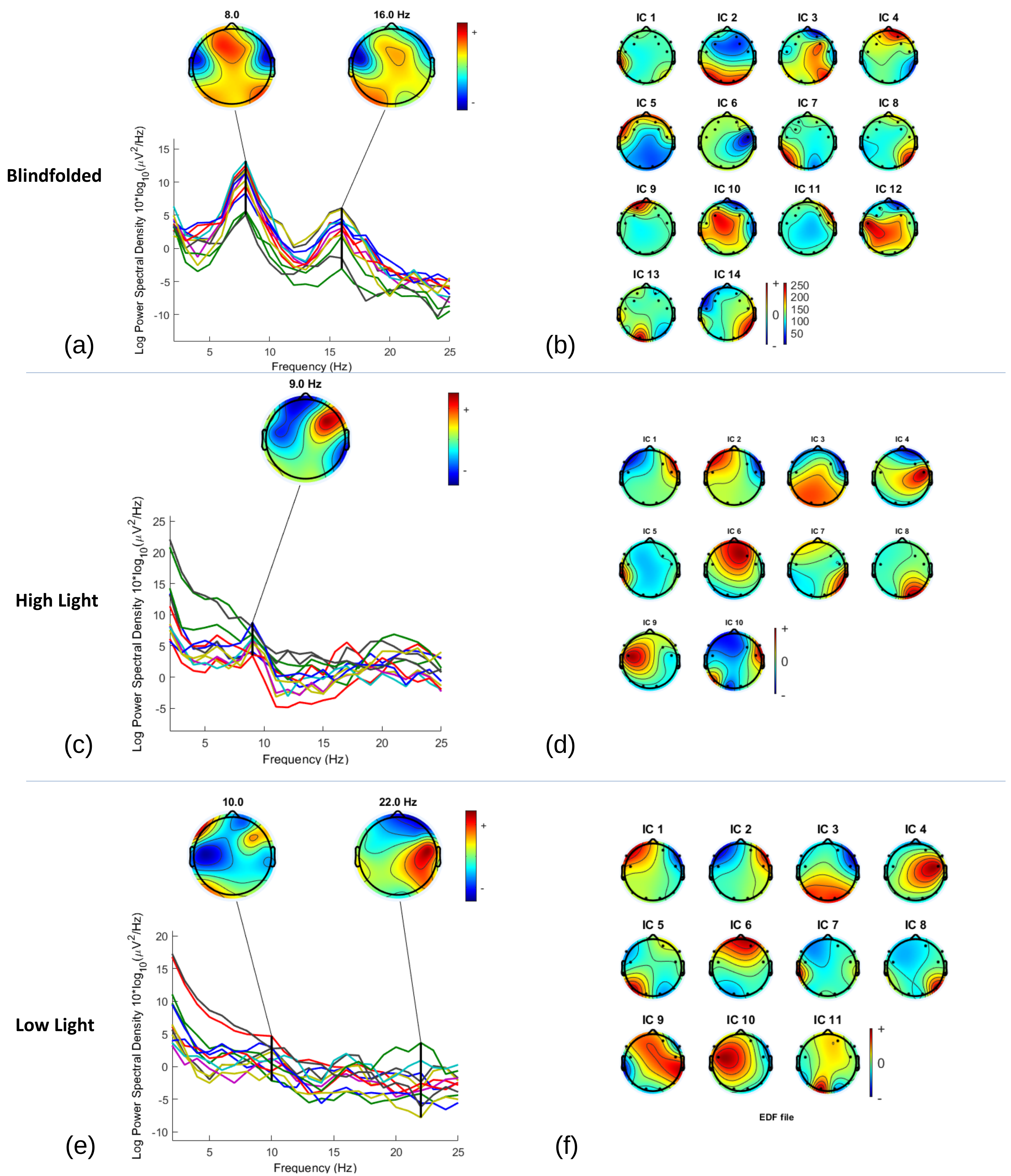

Figure 3. (a) Spectral density shown for the blindfolded trial. Notable frequencies 8 Hz and 16 Hz highlighted for emphasis. To the right (b), includes the ICA for the blindfolded trial, suggesting that channels 10 and 12 recorded the most activity during this task. During the high ambient light session (c), a spike in the 9 Hz can be seen. The high light ICA (d) shows channels 4 and 6 and 9 to be of relatively high activity. In the low light spectral density (e), a spike in beta rhythms at 22 Hz can be seen in addition to a smaller spike in the 10 Hz frequency. ICA of the low light trial (f) suggests that channels 4, 6, and 10 to be of notable activity, similar to the high light trial (d).

signals. One group has been able to utilize machine learning to identify changes in individual's attention state using passive EEG collected over a large timespan [14]. The combination of additional biosensors and machine learning-based data processing techniques is becoming known as ambient intelligence (AmI). That is, the capacity to synthesize information acquisition and processing from a variety of sources to produce useful outputs [15]. Many different types of sensors such as smart watches, sound sensors, and cameras can be leveraged to create a user-centric assisted living system, adaptive to a user's habits, gestures, and emotions [16]. EEG data is just one of many potential inputs that AmI will use to proactively support people in their daily lives.

To more fully realize the passive BCI, a few additional areas should be addressed. It is known that EEG can vary considerably between users and even between sessions of the same user. The integration of additional biometric features, such as heart rate, may potentially confound brain activity. It may be difficult for a developer to incorporate all of these features into a meaningful smart home platform. Therefore, a large number of EEG studies are required to data capital needed for machine learning algorithms to properly assign weights to relevant features associated with a particular command.

5. Conclusion

EEG has already been shown to be a well researched and standardized method of non-invasive BCI. The low-cost, portability, and relative ease of use off EEG based platforms continue to improve. In addition, modern machine learning techniques are addressing technical problems concerning pattern recognition and data analysis. The non-invasive nature of EEG, coupled with unobtrusive use, is key to the mainstream adoption and further development of this technology. Though the elderly and those suffering from neurological deficits stand to benefit the most from this technology, there is potential for anyone to use EEG to control smart devices. One of the key challenges is the skill requirement associated with training the user to associate a particular signal pattern with the desired action.

Although there are no inherit safety risks associated with using EEG devices, users should still demonstrate caution in interpreting EEG signals, particularly for neurofeedback and wellness monitoring applications. Lab-grade and commercial-grade devices may vary considerably, and the body of research on the former is considerably smaller [17]. Medical EEG interpretation continues to be an active area of neurological research. The growing consumer EEG device market makes many claims about user wellness that have not been rigorously lab-tested.

The distinction between EEG data that can be used to command a computer is all too blurry from the EEG signal that could potentially diagnose a neurological illness. The fact remains that EEG recordings are sensitive bio-metric data requiring secure storage. It is the responsibility of any bio-metric data gathering platform to adhere to best practices for managing sensitive user information.

In the future, a smart-home platform may incorporate a variety of sensing mechanisms and bio-metrics to anticipate and respond to the needs and controls of the user. The goal is to expand the feasibility of such systems by lowering barriers such as cost and skill requirements as factors. A passive BCI will ideally work out-of-the-box or with very little conscious training required, providing greater accessibility to all.

Acknowledgments

Thanks to Dr. Holly Matto and Dr. Nathalia Peixoto for use of the EPOC+ headset. Thanks to study participant Anastasia Osowski.

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