Novel Methods for EEG Visualization and Virtualization

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***Abstract*—Here we present several methods for representing electroencephalography (EEG) signals in a manner that is intuitive to non-scientists, in order to improve communication about the meaning of the underlying recorded signal. To support the use of various forms of EEG signal, we have developed a signal processing pipeline to filter noise and extract relevant, user-selected features. We provide two forms of presentation: a virtual reality (VR) system with a spatial audio and visualization, and a physical head model capable of displaying location and frequency-specific data. Examples are given for applications of the full system.**

***Index Terms*—Brain-computer interfaces, electronencephalography, virtual reality, evoked potentials**

I. Introduction

Brain-Computer Interfaces (BCIs) are an increasingly popular research area where signals from a persons brain are used to perform or inform an application. Electroencephalography (EEG) is a commonly used signal for BCI because of its high temporal resolution, noninvasiveness, and relative ease of measurement [1]. However, EEG suffers from noise and can be difficult to practically interpret and utilize, especially without expert knowledge. In this work, we developed and implemented a framework to virtualize and visualize EEG data in easily accessible modalities to enable use by a broader group of users.

Many EEG-based BCI applications currently exist for a variety of use cases. For example, neurofeedback training with EEG (where users are provided with feedback on different EEG parameters) has been used for various applications, including teaching meditation, reducing seizure rates, and improving sensorimotor control [2]. EEG can also be used to teach brain structure by visualizing the effect of external signals on brain function; for example, by using a typical steady-state visual-evoked potential (SS-VEP) paradigm, students can see the effect of a 10Hz light flash within the EEG signal [3]. EEG has even been applied as a cost-effective, noninvasive method for potentially detecting traumatic brain injury (TBI) by searching for specific marker patterns in EEG signal, though more research needs to be done [4] [5].

These applications, however, generally use limited methods for EEG processing and presentation. EEG is typically visualized as a set of linear plots of voltage. These plots are often corrupted by artifacts in the data and do not have an intuitive relationship with important features such as location and frequency, making them difficult to interpret by non-experts. Relevant features can be extracted from this raw signal for different tasks, but these visualizations (e.g., graphing power of different frequency bands for neurofeedback meditation) are often still not immediately intuitive and, depending on the feature, may require offline processing.

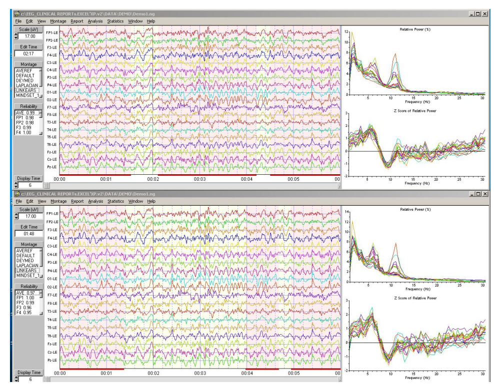

Fig. 1. On the left is a plot of raw EEG data; each row represents a channel. On the right is a plot of power of different frequencies, as might be used for neurofeedback training.

To address these limitations, we propose a general-purpose framework that provides interpreted EEG data for various applications in real-time within a layperson-comprehensible format. This framework consists of two components: a modular signal processing pipeline, and a virtualization method (e.g., spatial visualization/sonfication), to output the processed data. In the next Sections, we will explain this pipeline and the hardware implementations that we demonstrate.

II. Materials and Methods

Our framework consists of a series of modular blocks which are determined by the task to be performed and the hardware and software available. At a minimum, each configuration comprises an EEG device for collecting raw data, at least one signal processing block, and a hardware device for displaying the processed signal.

In this demonstration, we apply our framework to 3 example tasks. The first task is to determine whether a participants eyes

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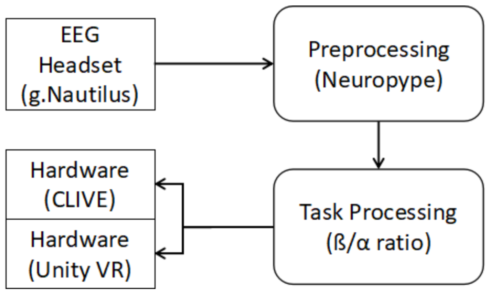


Fig. 2. Diagram of basic flow of our pipeline. Examples of each block are included in parentheses. Processing blocks can be composed of multiple subcomponents.

are open or closed using general beta/alpha ratio. This task is a classic test in fatigue detection [6]. The second task is to visualize the effect of an external signal on a participants visual and auditory cortices. In an SS-VEP, a 10Hz visual signal should elicit a 10Hz response in the primary visual cortex and thus be virtualized in the back of the head [7]. By contrast, a 10Hz audio signal, elicited in an analogous SS-AEP format, should be localized in the auditory cortex in the sides of the head. The third task extends the use of the beta/alpha ratio to a motor task: movement of the left/right hand elicits a decrease in alpha power in the opposite hemisphere [8].

Two different display modalities are possible for the resulting data: a virtual reality (VR) environment using the HTC Vive, and a physical head model, the Customizable Lighting Interface for the Visualization of EEG Signals (CLIVE). In all cases, we use a 32-channel g.Tec g.Nautilus headset with dry electrodes to collect the EEG signal from participants. This headset was chosen due to its ease of repeated setup, but any headset with any number of channels could also be used.

A. Signal Processing

Our demonstration implementation of the signal processing pipeline comprises several blocks. These blocks communicate information serially via Lab Streaming Layer (LSL), a data integration and synchronization network framework [9]. The first block is the EEG headset, which streams raw signal into LSL at 250Hz. The second block is a preprocessing block to reduce the overall noise in the signal. In this implementation, we use Neuropype (Intheon Labs, San Diego) to perform artifact removal and apply a bandpass filter of 1-40Hz to the signal before streaming the data to LSL; any real-time filtration system could be used in its place. The third block extracts task-specific features from the preprocessed data (the nature of these features and calculations for our specific demonstration will be discussed later). These extracted features are then sent to the hardware devices for display; in this case, either VR or CLIVE. For modularity, the features are sent in the same format regardless of the hardware used.

1) Beta/alpha Ratio: For the eyes-open/eyes-closed task, our pipeline computes a feature called beta/alpha ratio. In EEG, alpha frequency power is modulated by states of relaxation (increases when eyes are closed), and beta power is modulated by increased attentiveness (increases when eyes are open) [10].

Beta and alpha power are calculated by using Fast Fourier Transform (FFT) using Welchs method with Hanning windows to avoid discontinuities [11], with averaging across multiple sweeps to minimize the variance in the power spectral density. Each 2 second buffer of EEG data was separated into 3, 1 second windows, with the middle window overlapping the others by 50%, resulting in a 1 second delay from time of signal change to time of feature extraction.

2) Canonical Correlation Analysis (CCA): For the visual and auditory signal tasks, our pipeline computes a feature called steady state evoked potentials, which are neural responses to stimulation at a constant frequency, and can be used in visual, auditory, or even somatic modalities [12]. They are often used in BCI due to their high signal-to-noise ratio and low susceptibility to artifacts; example applications include spellers and computer control [13]. In response to a 10Hz visual signal, we want to extract a 10Hz EEG signal. or example, in response to a 10Hz visual signal, we want to extract a 10Hz EEG signal. Our implementation further decomposes SS-VEPs into the contributions from each electrode on the scalp such that the relation to brain location can be visualized.

In our applications, CCA is calculated by first taking data created using an Nx2 array representing both the sine and cosine of the desired frequency (10Hz) of the original stimulus (both signals are required so as to avoid phase problems with correlation). These guide signals are then related to the EEG signal from each channel, and an eigendecomposition of the composite signal is calculated to find correlations. The eigenvalues correspond to the maximum correlation, while the eigenvectors reflect the relative contributions of each electrode [13], allowing weighting based on response strength. In our method, a similar method is applied to both SS-VEP and SS-AEP.

B. Virtualization

1) Customizable Lighting Interface for the Visualization of EEG: CLIVE is a full-size physical model of a human head intended for intuitive visualizations of brain activity collected from an EEG headset in real-time. It is inspired by the topographical representations of EEG on the scalp that can be created by offline processing in such software as EEGLAB. In contrast, however, CLIVE provides a live demonstration of EEG via LEDs evenly distributed within a translucent head model.

The current generation of CLIVE was manufactured in two stages. First, an Ultem brain-shaped shell was created to hold 244 heat-tolerant individually-addressable NeoPixel LEDs connected serially; this shell was fitted atop a thick post to fit inside of the head model. Second, an oil-based room-temperature stable gelatin (Clear Ballistics, Fort Smith, AR) was heated and poured into a full head-shaped mold holding the LED-covered shell. The head model mold was then held at 120C for 36 hours to de-gas and left to cool and harden for an additional 26 hours.

LED inputs are based on a standard 24-bit RGB scheme. With 244 LEDs and a 1-bit transfer latency of 1.25s 600ns, the system is capable of updating at 135Hz, exceeding the human eyes typical 30Hz constraint and allowing adaptation to EEG feature changes essentially instantaneously. As CLIVE is only responsible for mapping incoming features to the LEDs and not the processing for extraction, the model is driven by an external Raspberry Pi 3 mounted in the base. Fig. 3 shows the LED circuit diagram.

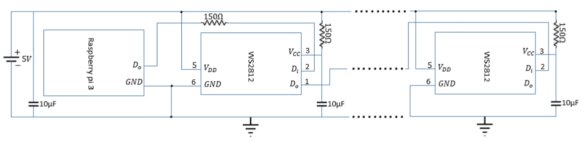
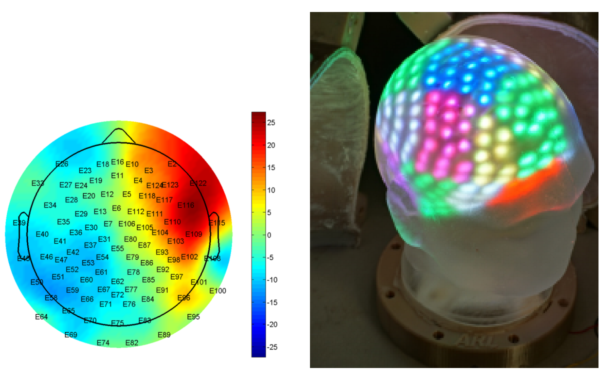


Fig. 3. LED wiring diagram for CLIVE

Because EEG headsets come in a variety of configurations, differing in channel count, channel location, and size, we had to determine a universal translation from electrode positions to internal CLIVE LED positions. To this end, we developed several mappings with various approaches. One mapping, for instance, consists of representing each electrode as a group of LEDs, thus creating a one-to-many internal relationship with large regions. A more intuitive mapping is an interpolation of true electrodes spacing to create a heat map for the scalp for real-time visualization. Due to the symmetry of the LED placements on the interface, any 10-20 based EEG system can be used.



(a) (b)

Fig. 4. (a) shows a typical topographical EEG scalp map. (b) shows CLIVE in operation.

Notably, live visualization is not a necessity for the CLIVE system, and thus allows visually appealing teaching methods to be used. Our use of LSL allows us to restream previously recorded data, allowing any number of offline processing methods to be applied but still visualized in realtime. This is especially useful for CLIVE, as some tasks (e.g. neurofeedback training for mindfulness meditation) may require the participants eyes to be closed and thus would not be suitable for live visualization. Using LSL, we would be able to induce a delay to allow the participants to see the visualization.

2) Virtual Reality: An alternative approach is VR, which we implemented in the Unity game engine. We first defined an acoustically-neutral room in the environment, and then implemented a virtual brain model imported from meshes created by 3d modeling software (Brainder for Blender [14]) based on actual MRI images [15]. n practice, participant-specific MRI scans could be used to provide a more accurate mapping representation. We use the Full Hemisphere mesh, rotated to align with the locations of electrodes. To allow light translucency through the brain model, we implement it with the defaults parameters except as shown in Table 1.

TABLE I
UNITY BRAIN MODEL SPECIFICATIONS

Material	EthanGray
Shader	Stanard(Specular)
Rendering Mode	Transparent
Smoothness	0.4
Source	Specular Alpha

In a typical demonstration, the participant wears an HTC Vive linked to a camera object in the VR environment via the HTC Vive plugin. The plugin handles motion tracking for both the headset and the HTC Vive controllers. Using spherical coordinates provided by the g.Nautilus, we map each electrode to a point on the brain to serve as a light and audio source. The shader combines light from these sources to color the brain model.

We use the Steam Audio plugin to provide positional sound at the camera/participant location for each audio source. Spatial audio works by using a head-related transfer function (HRTF) to alter the time at which a sound arrives at each ear, allowing people to localize different sound sources. In practice, although human visual acuity is such that people are capable of distinguishing light sources that are 1.75mm apart [16], our ability to localize sound depends on the location of sounds relative to the head and is overall much more limited [17]. Due to these limitations and to issues identified in early demonstration testing, in order to provide a coherent sound landscape within which audio sources can be distinguished, the number of audio signals is limited to an evenly-spaced 3x8 grid system.

C. Demonstration Tasks

To demonstrate possible use cases of the system, we performed the tasks listed above, using both live and restreamed EEG data. For both CLIVE and the Unity VR environment, we developed specific mappings of the extracted features to different parameters. For the eyes-open/eyes-closed task, we rescaled the beta/alpha ratio to a range of 0 to 1 for any given demonstration. In CLIVE, this ratio is mapped to a color. Each group of LEDs map this range of 0-1 to blue (0,0,255 RGB) to red (255,0,0 RGB). Thus, the colors of different LEDs change as the extracted ratio does, providing quick response to eyes closing and opening.

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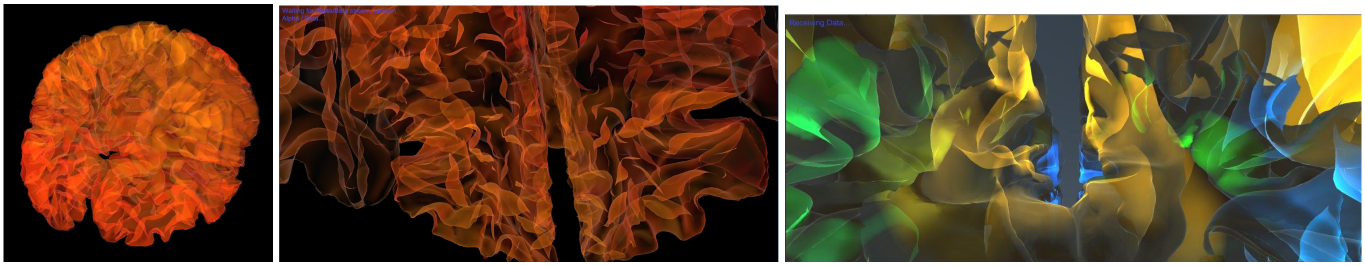

(a) (b) (c)

Fig. 5. (a) Outside VR brain model (b) Inside VR brain model. (c) During beta/alpha task.

The VR visual mapping functions similarly, mapping the ratio to a hue range between 240 (blue) and 360 (red) for each light source defined on the brain model; with its one-toone mapping, VR is able to quickly display a high-resolution representation. The VR audio mapping operates on bimodal scale instead. If the beta/alpha ratio for an electrode is between 0-0.5, the percussive source plays, with volume scaled on a 0-1 multiplier increased as the ratio approaches 0. If the ratio is 0.5-1, the melodic source plays instead, with its volume increasing as the ratio approaches 1. If the ratio is 0.5 precisely, neither audio source plays. Because humans are less able to localize sound than visual stimuli, we reduce the number of audio sources to eight distinct regions in the brain model.

For the external signal task, the primary purpose is to display the location of the response. Using CCA, we calculate the relative response of each electrode to a 10Hz signal. In both CLIVE and VR, this is visualized purely by intensity of light; LEDs and light sources in areas of the brain with a stronger response result in brighter visualization in those areas.

As proof of concept, we demonstrated these tasks at local presentations at Army Research Laboratory.

III. Applications

This work is motivated by the desire to make real time brain activity more accessible to non-expert users. This capability has several applications. For example, in teaching situations, such as classrooms and STEM demonstrations, it is often difficulty to relay the connection between the occurrence of external events and the human brain response to those events. By using a CLIVE system, students can easily see, in real-time, how, and where, these connections occur (e.g., visual cortex inside the head responding to a visual event). Similarly, it can be used for new technology demonstrations for non-scientists to showcase new ways of collecting EEG.

Within the medical domain, TBI/concussion at the time and site of injury are difficult diagnoses to make and have significant repercussions. This system would permit minimally trained personnel access to current neural data to help make these diagnoses at a relevant and useful time scale [5]. Further, there has been recent interest in mindfulness, meditation and other practices that attempt to modulate neural activity to provide optimal states and their relative changes in EEG [2]. Thus, an easily accessible visualization system such as ours provides an avenue for intuitive neurofeedback to facilitate these practices.

In the future, we envision extending this framework to more complex features of EEG, such as functional network connectivity, which has shown promise for potentially diagnosing various forms of psychiatric disease [18]. Due to the modular nature of our framework, we can incorporate such feature extraction tools as EEGNet to process signals depending on the application [19]

IV. Conclusion

In this work, we have introduced a general-purpose, highly intuitive framework for virtualizing task-related EEG data features in real-time. Additionally, we have provided implementations of three common BCI tasks in two primary hardware forms: a physical head model (CLIVE) and a VR environment with localized visual and auditory feedback. We are in the process of increasing the sophistication of these hardware implementations and envision extending our framework to new tasks with broader audiences in the future.

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