Human-Computer Interaction with Virtual Reality using Brain Signals Computing

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***Abstract*—The overall goal of this study was to determine whether the presence of Virtual Reality (VR) affects brain signaling as measured with an electroencephalograph (EEG) because this potentially could lead to a new way of accessing and utilizing the EEG biometric. There has been previous Human-Computer Interaction (HCI) and Brain-Computer Interface (BCI) research using EEG to collect brain signals and Alibaba has a digital marketplace that uses VR, but the brain signals relationship to VR is under-researched. Our research required a detailed set-up to capture valid EEG data and demonstrates the requirements needed to accomplish this initial research stage. Surface EEG signals were measured during a resting state, as well as an active cognitive state both with and without VR. A comparison of resting and active data samples will determine if the signal behavior is unique to VR stimuli.**

***Index Terms*—Virtual Reality, EEG, Cognitive, Brain-Computer Interface, Biometric, Human-Computer Interaction, Alibaba**

I. Introduction

For security purposes, it is essential to be able to authenticate that someone is who they claim to be [1]. There are, however, vulnerabilities to security systems based on user names and passwords or tokens (tokens are physical security objects such as a smart card or secure ID) [1]. Passwords can be hacked, and tokens can be lost [1]. Biometric authentication, such as fingerprint scanning, has become a popular security alternative to user name and passwords for security of mobile devices because of ease of use [2]. Table I identifies types of biometrics and provides categorically ranked columns to the right. The EEG rankings were added to the table [3]. This table shows that DNA scores high in several categories, including performance but low in the categories of acceptance by users, while signatures score low in performance but high in user acceptance [4]. But, like passwords and security tokens, biometric data can also be stolen. In 2015, the database containing the fingerprints of 5.6 million U.S. federal employees was breached [5]. The human body has a limited number of biometrics such as retinas and fingerprints [2] that once compromised remain permanently compromised [6].

Brain-based biometric authentication has the potential to change the way humans interact with their electronic equipment, if computers can authenticate a user's brain signals [7].

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TABLE I: Comparison of various biometric technologies with ratings High (H), Medium (M) and Low (L) modified by adding EEG to the original table [4]

Biometric Identifier	Universality	Distinctiveness	Permanence	Collectability	Performance	Acceptability	Circumvention	Security	Genotypic
DNA	H	H	H	L	H	L	L	H	H
Ear	M	M	H	M	M	H	M	M	H
Face	H	L	M	H	L	H	H	M	H
Facial Thermograph	H	H	L	H	M	H	L	M	L
Fingerprint	M	H	H	M	H	M	M	H	L
Gait	M	L	L	H	L	H	M	L	H
Hand Geometry	M	M	M	H	M	M	M	M	H
Hand Vein	M	M	M	M	M	M	L	H	L
Iris	H	H	H	M	H	L	L	H	L
Keystroke	L	L	L	M	L	M	M	L	L
Odor	H	H	H	L	L	M	L	H	H
Palm print	M	H	H	M	H	M	M	H	H
Retina	H	H	M	L	H	L	L	H	L
Signature	L	L	L	H	L	H	H	M	M
Voice	M	L	L	M	L	H	H	M	H
EEG	H	H	H	H	H	M	L	H	H

The brain can provide an unlimited number of passwords [2] and users would no longer need to enter one via a peripheral device such as a touch screen, keypad or speech recognition system. The process of biometric authentication is shown in Figure 1 on page 2. The top of the figure shows EEG (and possibly VR) biometric data being collected, extracted and stored. The bottom of the figure shows a live scan using the same parameters being compared to the stored biometric data for verification. In this example, the verified data is sent to storage to provide an audit trail and to business applications [8]. In short, biometric authentication methods match an individual's genetic traits or behavioral characteristics with data that have previously been captured, in the database or on a token [9].

EEG signals are attractive for biometric authentication because they are nearly impossible to fake, are unique, and

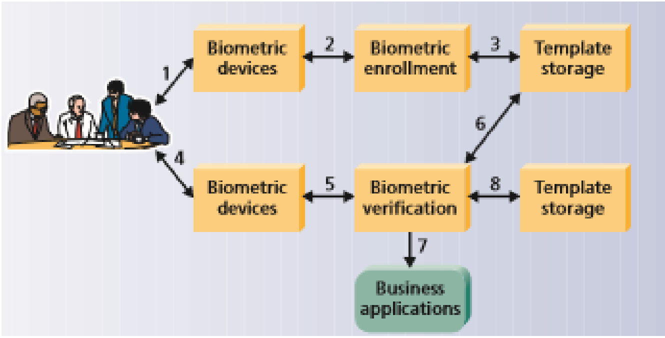

Fig. 1: Biometric process [8].

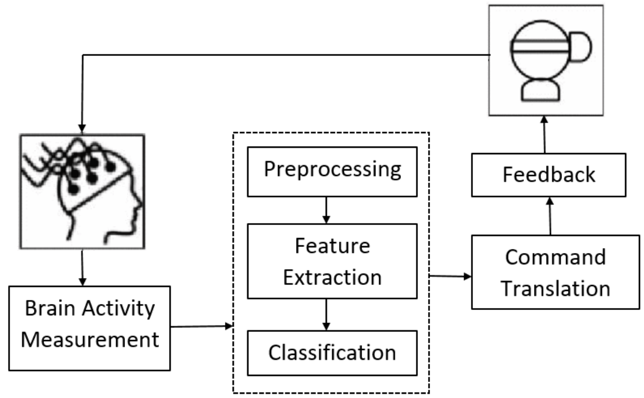

Fig. 2: Model of the online BCI redrawn for this study [11].

can be obtained with a non-invasive surface scan. An EEG signal detects the electronic field generated by the firing of neurons in the brain. Advancements in EEG make it easy to find repeatable and stable brain signal patterns that through machine learning can be used for identity verification [1]. Referring to Figure 1, an EEG-based biometric can be set by showing the individual three images [2]. If the EEG-based biometric data is stolen, the biometric can be reset with another three image biometric recording session [2]. Notably, every brain responds differently to the same set of images [10].

Figure 2 shows a model of an online BCI as a closed loop. An EEG collects signals, patterns and cognitive state measurements, which are sent to a preprocessing stage where machine learning is used to extract features and make a classification. At this stage machine learning takes data, such as biometric, cognitive states and behavior patterns, and output a command translation, which is sent to the interface and back to the user [11]. Feedback from an EEG-Based measurement could be a biometric authentication. A potential application of the current research might be with a company such as Alibaba where shoppers select an item in a VR environment by looking at it for a long enough time and the moving their head to make transactions A BCI could be a brain-based password that secures payment information stored on a VR headset to prevent unauthorized purchases [2]. A BCI could be a brain-based password that secures payment information stored on a VR headset to prevent unauthorized purchases [2].

II. Literature Review

The lead researchers for this study have published research on BCI and VR [11]. At their suggestion, existing datasets [12] [13] were reviewed for this study.

The results from the EEG and VR relationship have been shown to vary depending on the age of the person as it relates to the development of the brain frontal cortex [14] and could be used for biometric authentication. Specifically, the development of the frontal cortex in relation to arousing and non-interactive VR as measured by EEG and EEG + VR as the brain continues to develop to adult status [14].

Existing research supports concepts of this study in that assessing memory load using neural network pattern recognition can be done successfully using EEG equipment [15]. Moreover, it has been found that EEG provides a non-muscular chain that allows for the successful connection of BCIs to the outside world [16]. A study by Gevins [15] examined the working memory load during computer-based tasks with EEG methods. A distinctive network pattern of computer-based work was recognized by applying it to EEG spectral features [15]. The study involved participants performing high, moderate and low load working memory tasks and found more than 80 percent of their test data, segments associated with a moderate load could be discriminated from a high-load or low-load data segments [15]. The researchers found that mental effort increased with task difficulty and could be associated with the cortical resources the brain allocated to the task at hand [15].

A survey of signal processing algorithms conducted by Bashashate [16] sought to find the key electronic brain signal processing components in BCI, what signal processing algorithms have been used in BCI, and which signal processing techniques have received more attention, found that BCIs aim at providing a non-muscular channel for sending commands to the external world using the EEG activity or other electrophysiological measures of brain function [16]. Researchers noted that the methods used to process brain signals are a strong factor in the successful operation of a BCI system [16].

Brain signal biometrics could be used with other authentication methods in a multi-factor authentication system. A multi-factor biometric authenticating device generates error correction by sampling multiple biometrics then generating a secret encryption key for encrypting user data [17]. There is already research into a continuous function gate to protect users involving biometric methods such as thumbprint, voice print, digital photos and other such stored identifiers [18].

Other research into biometrics has been done using EEG to collect brain signals from 8-channels [7]. That research showed visual stimuli collected using EEG can produce a high-quality brain-based biometric for authentication [7]. VR is an interactive computer-generated experience, often with audio or visual stimuli. There are side effects to VR; for example, driving simulations can result in motion sickness [19].

Our research using VR will utilize a state recognition factor. Emotion recognition systems using brain and peripheral signals improve the results of EEG in the correlation dimension [20]. Control over the cognitive state of the user using the Cognitive Event-RElated Biometric REcognition (CEREBRE) protocol allowed for very high accuracy for event-related potential (ERP) biometric identification [10].

There is research-using EEG as a handicap aid and for medical signaling [21]. A study [22] examining the VR environment for evaluation of a daily living in brain injury rehabilitation found that VR was a reliable method of collecting information from persons that had experience with a traumatic brain injury [22]. This suggest that brain-based biometric authentication could also be utilized by persons with injuries of the brain.

III. Methodology

Data collection and storage was designed in accordance to IRB requirements [23] for human participants. Participant data was coded to protect patient confidentiality and stored securely. All researchers completed IRB required courses and received Collaborative Institutional Training Initiative (CITI) [24] Certification. The experiment was thoroughly explained to, and informed consent obtained from, each participant.

Questionnaires were provided in order to garner basic demographic information (age, gender, handedness, vision [normal, corrected to normal, or acceptable non-corrected], education level). Additional questions were asked in order to identify factors, which can affect neuronal activity in the brain and may potentially produce outliers in the data. Participants were asked to self-report (today, regularly, never, or yesterday) on their consumption of alcohol, coffee, tea, tobacco, and other drugs/medicines. They were also asked about having attentional, neurologic, or psychiatric conditions, as well as how many hours of sleep they had the night before, their normal hours of sleep, and level of alertness (high, medium, or low). Participants were also asked to consent to distribute their physiological recordings for this research.

A. Participants

Sixteen people participated in this study (age range 20-35; 6 female, 10 male; 11 right-handed, 5 left-handed). All of the participants had normal or corrected to normal vision (6 wear glasses, 2 wear contacts) and a college degree (4 Bachelor, 11 Master, 1 PhD). Most participants drink coffee (4 today, 6 regularly, 4 regularly/today, 5 never, 3 occasionally/not today, 1 yesterday), and more drink black or green tea (10 today/regularly, 3 occasionally/not today, 3 never). All were well rested (mean of 6.7 hours of sleep the night before; mean of 7.5 normal number of sleep hours). Participants reported feeling alert during the experiment (7 high, 8 medium, 1 low).

B. Materials

This study used an OpenBCI EEG Ultracortex Mark headset. The Ultracortex is an open-source 3D-printable headset intended to work with the OpenBCI system. Eight electrodes provide eight channels on the OpenGUI screen. The headset is capable of recording research grade brain activity (EEG). The OpenBCI USB Dongle and WiFi shield communicate via WiFi and Bluetooth with the RFDuino on the Cyton board. The dongle establishes a serial connection with the on-board FTDI computer chip to the OpenBCI GUI. Both the device and the dongle need to be connected to the same WiFi network. VeeR Cardboard is used to play a VR video.

OpenBCI GUI software was used for collecting data for the VR and the non-VR condition. MNE-Python, NumPy, and Pandas were utilized for analyzing the data with reprocessing using machine learning techniques. Figure 3 shows an example of live streaming data.

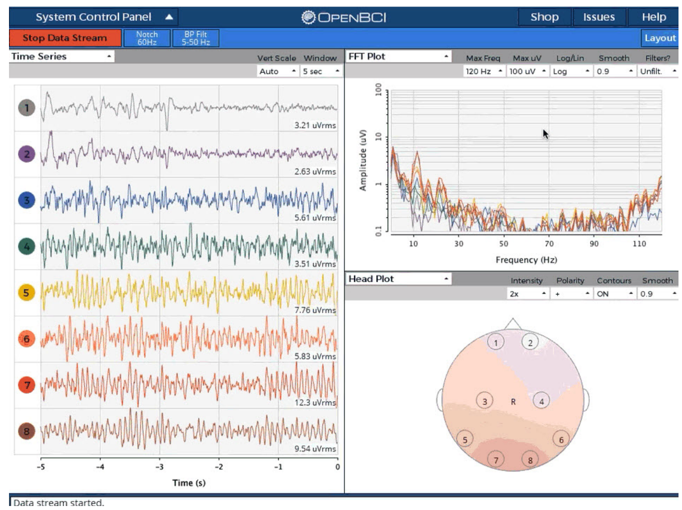

Fig. 3: OpenBCI Python GUI [25].

C. Experimental Procedure

The procedure was explained to each test participant, the OpenBCI headset was placed on the participant's head and researchers confirmed that all 8-channel sensors were placed properly so that there were no errors in the data collection mechanism. Once comfortable, participants were instructed to rest for 60 seconds, taking deep breaths for 30 seconds with their eyes closed and for 30 seconds their eyes open. After the resting period the participant was either given the Google Cardboard for VR content or the content was provided on a laptop for non-VR. In this experiment, The Pull video was selected from the VeeR VR global VR/360 content community website. The VR/non-VR session, content was played for exactly two minutes with the same video and the data streaming provided using the OpenBCI GUI application. Figure 4 and Figure 5 show how the VR/non-VR sessions were conducted. Once data streaming stopped, a text file was generated containing the data of 8-channels in float (converted from analog signals) along with time stamps in milliseconds (ms). The difference between VR and non-VR is not apparent just by looking at the text files as can be seen comparing Figure 6 to Figure 7. Both figures were collected for this study and provide an example of why machine learning was required to process the data.

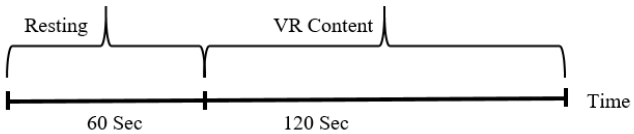

Fig. 4: VR Experiment Session.

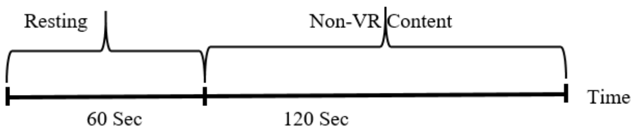

Fig. 5: Non-VR Experiment Session.

```
% First column is a sample index/number of instances
% Last column is a timestamp
% Other columns are 8-channel EEG Data

0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0, 14:19:15.659
1,42914.52,187500.0,9868.52,17651.51,187500.0,17071.01,45300.7,43459.19, 14:19:15.674
2,42926.9,187500.0,9883.58,17657.32,187500.0,17069.15,45321.63,43470.61, 14:19:15.681
3,42933.36,187500.0,9886.91,17653.5,187500.0,17064.24,45315.81,43471.28, 14:19:15.681
4,42933.9,187500.0,9882.35,17641.74,187500.0,17044.93,45330.34,43443.25, 14:19:15.689
5,42949.52,187500.0,9889.69,17647.04,187500.0,17038.15,45321.27,43438.33, 14:19:15.689
6,42957.35,187500.0,9900.93,17642.14,187500.0,17032.81,45333.2,43437.66, 14:19:15.697
7,42957.66,187500.0,9917.67,17645.0,187500.0,17033.39,45376.79,43451.77, 14:19:15.697
8,42943.69,187500.0,9920.17,17636.96,187500.0,17022.66,45374.31,43438.91, 14:19:15.703
9,42939.67,187500.0,9930.3,17633.54,187500.0,17015.29,45385.19,43434.27, 14:19:15.703
10,42953.32,187500.0,9947.11,17637.6,187500.0,17018.82,45396.64,43436.84, 14:19:15.711
```

Fig. 6: EEG + VR data collection sample showing the index number, the 8-channels and the time stamps.

```
% First column is a sample index/number of instances
% Last column is a timestamp
% Other columns are 8-channel EEG Data

0,0.0,0.0,0.0,0.0,0.0,0.0,0.0,0.0, 14:37:53.114
1,26637.53,-187500.02,-6497.81,-1296.89,187500.0,-5843.55,32660.44,16941.93, 14:37:53.128
2,26635.14,-187500.02,-6495.69,-1302.39,187500.0,-5848.42,32647.16,16943.43, 14:37:53.134
3,26627.65,-187500.02,-6511.2,-1314.04,187500.0,-5861.7,32634.39,16928.41, 14:37:53.135
4,26629.2,-187500.02,-6514.64,-1311.11,187500.0,-5864.14,32630.3,16922.71, 14:37:53.141
5,26631.39,-187500.02,-6513.68,-1311.02,187500.0,-5861.61,32614.46,16898.79, 14:37:53.141
6,26627.01,-187500.02,-6519.71,-1322.58,187500.0,-5868.47,32616.87,16908.63, 14:37:53.149
7,26648.44,-187500.02,-6507.15,-1298.9,187500.0,-5854.17,32629.75,16926.51, 14:37:53.149
8,26647.95,-187500.02,-6510.66,-1303.49,187500.0,-5854.91,32614.57,16907.6, 14:37:53.156
9,26653.4,-187500.02,-6516.92,-1307.69,187500.0,-5855.11,32610.99,16916.25, 14:37:53.156
10,26659.71,-187500.02,-6516.11,-1306.33,187500.0,-5853.99,32602.68,16904.45, 14:37:53.163
```

Fig. 7: EEG + non-VR data collection sample from the same participant.

D. Pre-processing

The data collected resulted in 32 text files (1 VR and 1 non-VR file per participant). Figure 8 is a custom work-flow diagram created to show the stages of pre-processing beginning with the data collected in RAW form. The RAW channels are depicted in Figure 9. Three columns of auxiliary data and a time-stamp column were removed leaving the columns containing the 8-channel EEG signals of participants.

The data were then pre-processed. First, bad channels (i.e. those not working properly) were removed using MNE (see Figure 10 and Table II on page 5), as were artifacts from eye and muscle movement.

A notch filter was applied to remove power line noise from the data. The visualization of channels after applying notch

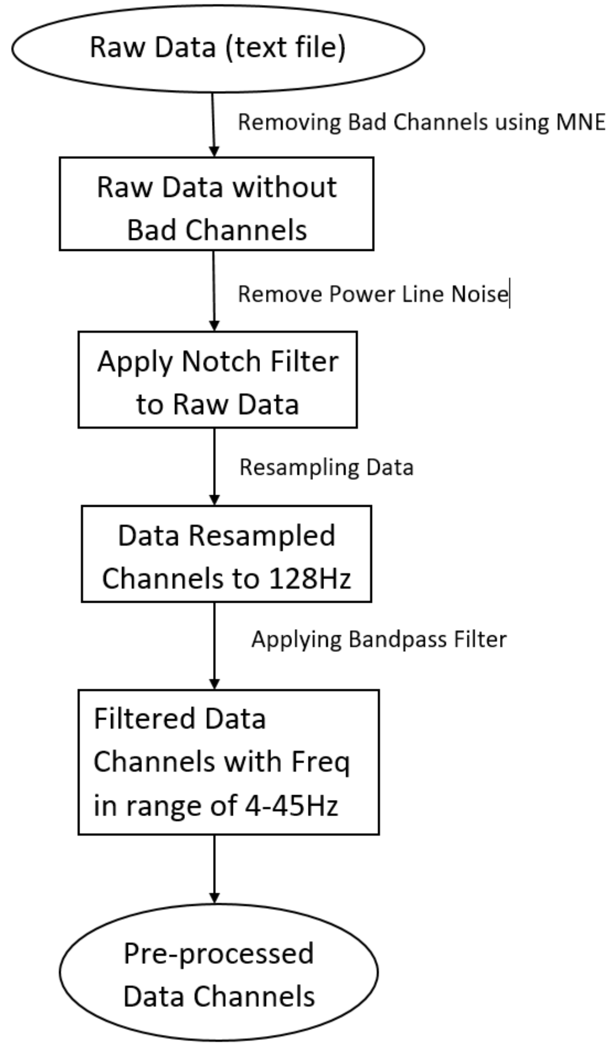

Fig. 8: Custom pre-processing work-flow.

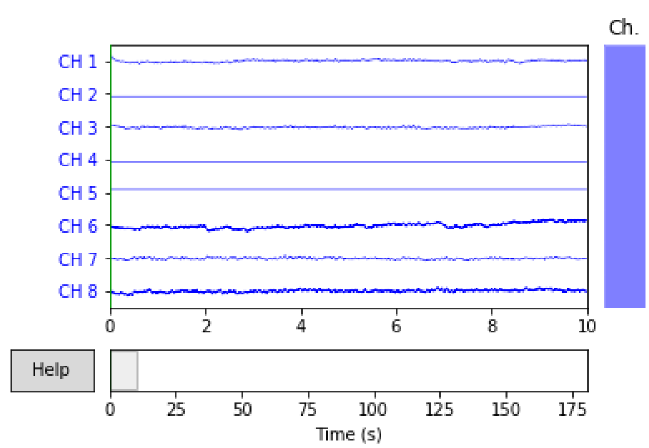

Fig. 9: RAW Channel Visualization.

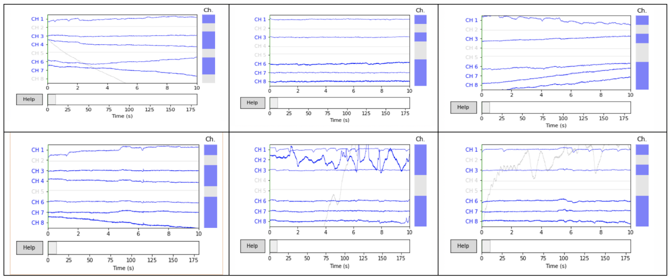

Fig. 10: Bad channel removal visualization for some participants - 1st row for VR Session and 2nd row for a non-VR Session.

TABLE II: Good channels (√) and bad channels (X) for all participants

Subjects		Ch1	Ch2	Ch3	Ch4	Ch5	Ch6	Ch7	Ch8
S1	VR	√	√	√	√	X	√	√	√
	NonVR	√	√	√	√	X	√	√	√
S2	VR	√	X	X	√	X	√	√	√
	NonVR	√	X	X	√	X	√	√	√
S3	VR	√	X	X	√	X	X	X	X
	NonVR	√	X	X	√	X	X	X	X
S4	VR	X	X	X	√	√	√	X	X
	NonVR	√	X	√	X	√	√	√	√
S5	VR	√	X	√	√	X	√	√	√
	NonVR	√	X	√	√	X	√	√	√
S6	VR	√	X	√	√	X	√	√	√
	NonVR	√	X	√	√	X	√	√	√
S7	VR	√	X	√	X	X	√	√	√
	NonVR	√	√	√	X	X	√	√	√
S8	VR	√	X	√	X	X	√	√	√
	NonVR	√	√	√	X	X	√	√	√
S9	VR	√	X	√	X	X	√	√	√
	NonVR	√	√	√	X	X	√	√	√
S10	VR	√	√	√	√	√	√	√	√
	NonVR	√	√	√	√	√	√	√	√
S11	VR	√	√	√	√	√	√	√	√
	NonVR	√	√	√	√	√	√	√	√
S12	VR	√	√	√	√	√	√	√	√
	NonVR	√	√	√	√	√	√	√	√
S13	VR	√	√	X	√	X	X	√	√
	NonVR	√	√	X	√	X	X	√	√
S14	VR	√	X	X	√	X	√	√	√
	NonVR	X	X	X	√	X	X	X	X
S15	VR	X	X	X	√	X	X	X	X
	NonVR	X	X	X	√	X	X	X	X
S16	VR	√	√	√	√	√	X	√	√
	NonVR	√	√	√	√	√	X	√	√

filter can be found in Figure 11. The data were then re-sampled at 128Hz and the power spectral density of the re-sampled data were plotted to get a better sense of frequency vs power. Figure 12 shows that channels have been re-sampled at 128Hz.

Next, a dual (low-pass and high-pass) bandpass filter was used to attenuate the 4-45Hz frequency range, converting signals to a low frequency resulting in the RAW data being turned into pre-processed data. The power spectral density of the processed data can be found in Figure 13.

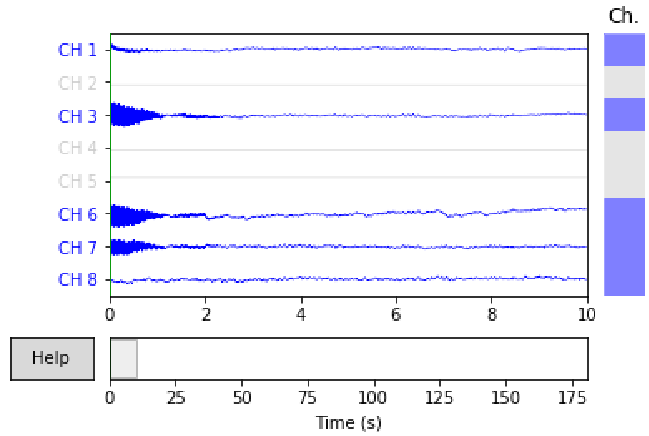

Fig. 11: Applying a notch filter on RAW data to remove any power line noise.

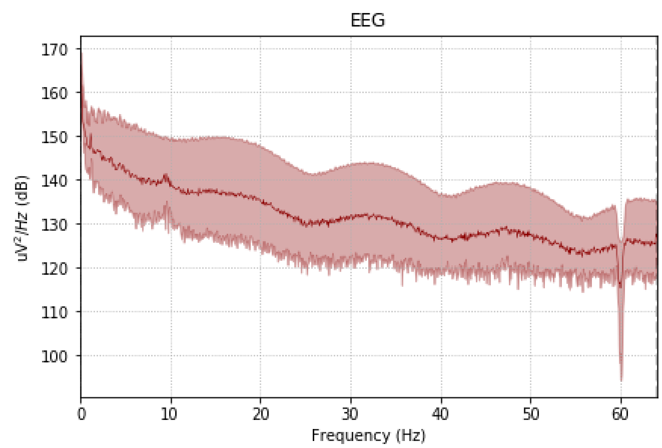

Fig. 12: Re-sampled channels to 128Hz.

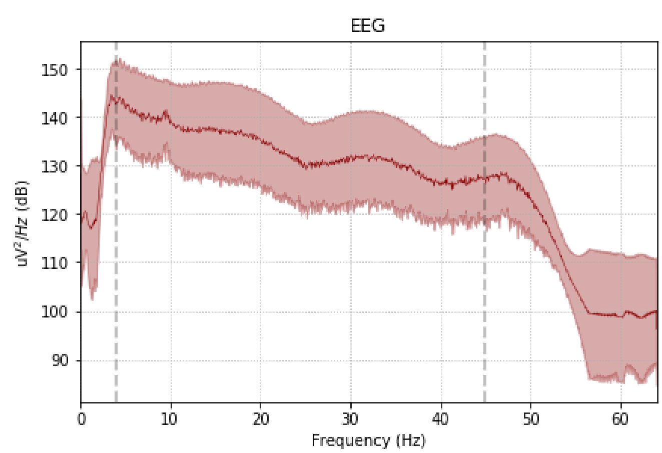

Fig. 13: Applying a bandpass filter to attenuate signals in the range of 4-45Hz.

IV. Conclusion

In conclusion, our research focused on data collection methods, ensuring quality and consistency. Our research also focused on pre-processing the data to make it ready for EEG analysis. Every participant's EEG channels are distinctive as shown in Table II.

V. Future Work

If measurable differences are found in comparing the VR and non-VR data collected in this study, then one possible application to HCI and BCI development is to improve the feasibility of using EEG-based authentication systems. Once completed, this study's machine learning analysis can be compared to other EEG collections, such as the Dataset For Emotion Analysis Using Physiological and Audiovisual Signals (DEAP) [12] and the EEG Motor Movement/Imagery Dataset [13].

Lack of sleep has been linked to the buildup of plaques in the brain which is a pathologic hallmark of Alzheimer's disease [26]. Another cause for the buildup of these Alzheimer's type plaques in the brain is cramming for exams [27]. Studies using the same stimulus over time could be able to detect detrimental brain changes before there are overt symptoms [26].

Brain-based password research found that biometric authentication could be done using as few as three EEG sensors with an application of smart mobile head wear [2]. This uses visual stimuli to produce reliable brain responses [6], with unique features in the mobile headset to analyze those brain responses [6]. This then divulges the biometric credential, cancels the credential and resets a new brain password with the mobile platform [6]. A lightweight headset such as this which uses three sensors may find greater user acceptance [2] than other high-performance biometrics. Thus, future research might look to reduce the size while simultaneously increasing the performance of biometric authenticating devices.

Our study uses inexpensive VR and software that offers a mild VR experience. VR also known as augmented reality (AR) primarily uses visual and sound as sensory stimuli. An example of a more expensive VR product is the Looxid Labs prototype LooxidVR which is being marketed as an EEG and VR research tool [28]. The LooxidVR, shown in Figure 14, is a 6-channel EEG-base headset that combines EEG, VR and eye-tracking cameras (our research filters out eye movement as unwanted noise) [28]. This offers an option for future research involving a much more vivid user VR experience.

This new EEG-VR headset system has been engineered specifically for research in areas such as pain relief and dementia. It's planned use is to test a BCI device in VR before it is installed physically, to insure it is comfortable and ergonomic. This brand new LooxidVR system is not yet widely available but represents a potential future direction for this research, such as developing brain-based passwords from VR retail shopping [2] or to interact with avatars [30].

Fig. 14: LooxidVR headset system for EER-VR research. [29].

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