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Case Report

Case Study - Brain-Computer Interface Applications Research

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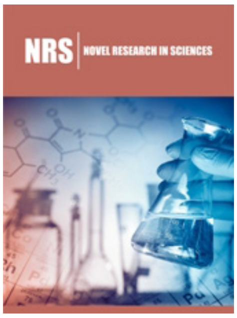

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History of BCI

Brain-Computer Interfaces (BCI) refer to the detection and implantation of brain signals and technology. The first implementation demonstrated and described in an academic setting was in 1964 by Dr. William Grey Walter of the Burden Neurological Institute of Bristol, who adapted Dr. Hans Berger's (of the Friedrich Schiller University of Jena) research from 1934 on Electroencephalogram (EEG) technology. This first demonstration from Dr. Walter had patients with "electrodes connected directly to the motor areas of a patient's brain [1]. The patient would then "press a button to advance a slide projector," making a neural connection that the EEG recorded. Upon enough presses, Dr. Walter would then connect the slide projector to the EEG directly, having the slides advance whenever the patient would make the neural connection to advance the slide. This connection would end up being long before the patient would normally press the button, introducing a way to control long before motor movement actually would occur, sparking the beginning of BCI [2]. 58 years later, in 2022, BCI still has much of its' roots in the medical field. Mamunur Rashid in Current Status, Challenges, and Possible Solutions of EEG-Based Brain-Computer Interface [3] discusses how the current state of BCI is "not limited to medical applications however, and hence, the research in this field has gained due attention." This same article discusses current research in the field, including control of wheelchairs in Fernández-Rodríguez et al. [4], control of mobile robotics by Bi et al. [5], biometrics by Alariki et al. [6], and pertinent to our focus, virtual reality and gaming by Kaplan et al. [7], Ahn et al. [8], and Cattan et al. [9], which will be further discussed in the "Recent Developments" portion of this paper.

The future of EEG and BCI relies heavily on solving the issues of high Signal-to-Noise Ratios (SNR). Dr. Rashid describes this as "amongst the greatest challenges in EEG-based BCI application studies." Mridha et al. pulled a summary of recent surveys and reviews on BCI technologies, drafting in their research a list of challenges [10]. Training time and fatigue, precariousness of surgery if the sensor in semi/fully invasive, and signal processing were the top challenges among 8 studies in the past three years. This will be further discussed in the "Analysis of Limitations" portion of this report. P Arico et al. discusses the future direction of BCI in terms of its' applications [11], including promising results in the field of driving, evaluating "the ability to perform effective teamwork," training and assessments, gaming, and "Neuromarketing" (consumer science, or the field of studying brain signals during the observation of advertisements to improve their effectiveness).

Existing Devices and Approaches

In R. Millan et al, 2020, the various approaches to BCI are discussed and gives a thorough representation of the various options for capturing brain signals [12]. The three types of BCI currently researched are split via how invasive, or how the apparatus to record the signals is installed, the procedure is. EEG, as discussed earlier, is considered non-invasive, as it uses electrodes and sensors that sit on the hair or exposed skin of the scalp to record data.

Electrocorticographic signals, as discussed by researcher Gerwin Schalk, "is acquired by placing electrodes underneath the skull, either above (epidural) or below (subdural) the dura mater, but not within the brain parenchyma itself." This is considered semi-invasive, as we must place technology within the skin but does not require a full placement within grey matter [13]; (Figure 1).

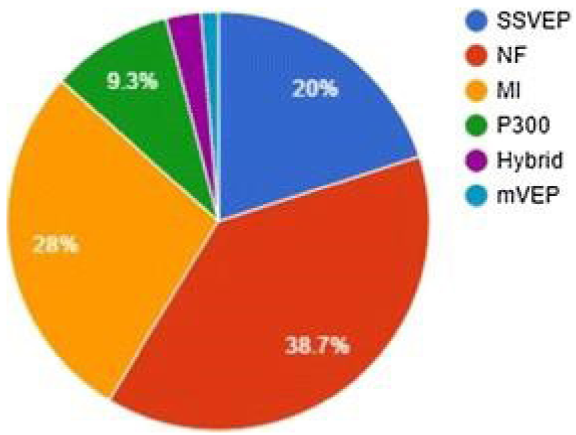

Figure 1

Non-Invasive

EEG

Electroencephalogram Brain Computer Interfaces (EEG BCI), and BCI as a whole comprise of five components, as described by Dr. Mridha: "brain activity measurement, preprocessing, feature extraction, classification, and translation into a command [10]. First, the signals given off by brain activity must be captured somehow (in the case of EEGs, this is through surface-level sensors. This data contains noise and artifacts, of which are eliminated through pre-processing (discussed further in "Analysis of Limitations."). Feature Extraction aims to take this "cleaned" data and sort the signals into values used to describe the various elements of the signal. These values are given along with the "cleaned" data to a machine learning/neural network algorithm to be classified and sorted according to these values. This organized and classified data is then passed to a device to result in some command (in the example with Dr. Walter, this command would be to move to the next projector slide) [10].

SSVEP vs P300

In Guger et al. [14] the question of SSVEP applications in BCI is initially discussed. The study, consisting of fifty-three volunteers, ran using electrode caps as configured in the image above, running LED simulations and volunteers were asked to focus on various signals and stimuli given by the researchers. This study found that in terms of training and focus, "all of the subjects who participated can achieve acceptable accuracies with SSVEP based BCIs after a very short training interval, and most subjects could attain 100% peak accuracy [14]. For SSVEP, the main focus for performance is on signal detection time and accuracy. Zhao et al. [15] discusses a direct comparison of direct control BCI for P300 and SSVEP. This study found that "The SSVEP model yields more rapid response to visual stimuli and is nearly independent of channel selection, but the number of the classifiable targets that can be displayed… is limited. Meanwhile, the P300 model can provide more classifiable targets and demands even less training, but response time is slower because it requires flashing stimuli one by one. While both can be implemented separately, a 2013 study from IEEE found that "data analysis results showed that combining P300 potential and SSVEP significantly improved performance of the BCI system in terms of detection accuracy and response time [16]. Another 2020 study on BCI controlling for Emotiv experiments found "combined classification results from SSVEP and P300 improved the reliability in classification for controlling external applications in a time window of three seconds [17]. The introduction of P300 alongside SSVEP improved accuracy for both studies, however the introduction of P300 would result in short delays from introduction of stimulus acquisition to device command.

MEG

While EEG recorded signals have distortions and noise due to hair and tissue between the signals and the sensors, magnetoencephalography cuts through this noise via whole-head neuroimaging utilizing "sensitive magnetometers and gradiometers to record the magnetic fields associated with intracellular post-synaptic neuronal currents in the brain [18].This results in reduced noise and higher accuracy and is often used in speech-related research due to its capability of capturing speech signals in fast and efficient ways compared to EEG. The biggest concern is the cost and size. Although research is currently underway and recent studies show promise of smaller, portable MEG devices [19], current devices are often costly and take entire rooms to implement.

Semi-Invasive

ECOG

In a 2011 study published by IEEE, electrocorticography is described as obtaining "activity recorded directly from the surface of the brain" [20], however requires invasive surgery and monitoring to place these electrodes and sensors on the surface of the brain. This necessary surgery requires clinical monitoring and medical expertise to stabilize patients as these are implemented and monitored. ECoG is often used in research on epileptic patients or patients with brain related medical issues [20].

Popular Brain Sensor Devices

Emotiv Offerings (HTTPS://WWW.EMOTIV.COM/)

Emotive is the more commercialized of the research EEG headsets, and also ranges to be some of the most expensive. The three available for purchase on their website listed above are the Insight, a 5-channel EEG that wraps around the ears, the epoch, a 15channel EEG covering around the skull, and the Epic Flex, with 32-channels. The Insight retails for $499.00, the epic retails for $849.00, and the Epoc Flex depends on type of cap for pricing, the Saline sensors retailing for $1,699.00-1,799 and the gel sensors retailing for $2,099.00 and offers portability. Research that utilized this headset are Performance of the Emotiv Epoc headset for P300-

based applications [21], 2013, An Investigation on Non-Invasive Brain-Computer Interfaces: Emotive Epic+ Neuroheadset and Its Effectiveness [22], 2021, A robust and reliable online P300-based BCI system using Emotiv EPOC + headset [23], 2020.

Openbci (HTTPS://SHOP.OPENBCI.COM/COLLECTIONS/FRONTPAGE)

Described by John La Rocco in his study A Systemic Review of Available Low-Cost EEG Headsets Used for Drowsiness Detection in 2020 [24], Open BCI consists of an Open BCI board that 3D printable open-source headsets can utilize, capable of using 4, 8, or 16 EEG channels, and requires "assembly prior to use, and therefore is not as widely used as readily-purchased consumer devices, but it theoretically allows greater customization." The pricing for Open BCI depends on what a user would want to purchase and use the headsets for. Boards start at $694.99 for a basic 4-channel board and increase up to $1,424.99 for a 16-channel board. Starter kits range from the "DIY Neurotechnologist's Starter Kit" at $1,284.99 to the "All-in-One Biosensing R&D Bundle" at $2,970.99. Notable research for BCI and VR are Impact of screen size on cognitive training task performance, 2021 [25] Connecting the Brains via Virtual Eyes: Eye-Gaze Directions and Inter-brain Synchrony in VR, 2021, [26] and Connecting the Brains via Virtual Eyes: Eye-Gaze Directions and Inter-brain Synchrony in VR, 2021 [27].

Analysis of Limitations

In the field of BCI utilized for gaming, the main limitations many researchers face is that of stability and consistency in using these systems. In many cases, BCI is reported to cause a "high level of fatigue and demands high concentration or attention to stimulus, and that it has a very low information rate [28]. Much of the consumer-focused EEG can see similar results however without supervision and precise implementation on someone, many of these sensors may be off and in multiple journals, increase of noise and interference was a high barrier to entry [28].

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