ISSN: 2754-6659

Journal of Artificial Intelligence & Cloud Computing

SCIENTIFIC Research and Community

Review Article

Open Access

Brain-Computer Interface, Generative AI (GAI)

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ABSTRACT

Brain-computer interface (BCI) is an interface (or sort of a system) by which humans can communicate with computers. The real question arises about why humans must communicate with the computer via brain signals. There are over a million or more people suffering from diseases or malfunctions of motor ability where mobility is limited, or there is no mobile at all. This interface allows these individuals to communicate with the outside world. Such diseases would rise yearly as more techniques and methods become available to diagnose them. While there is no cure for such injuries or diseases, there may be a stopgap to fill the communication void. We take communication for granted, whereas a person with limited mobility is a boon.

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Received: November 10, 2023; **Accepted:** November 16, 2023; **Published:** November 23, 2023

Keywords: Brain-Computer Interface (BCI), EEG, Neural Network, Generative AI (GAI)

Introduction

The human brain is a piece of engineering that cannot be replicated, and years to come before scholars at its full potential can understand it. The brain controls all the motor movements within the body, including most of the muscle movements. Persons with such disability would have their muscle movement rendered affected, not able to perform their day-to-day activities without any external help. In the ordinary world, anyone can communicate with computers using a keyboard, mouse, and such devices, which enable them to explore. Still, for persons with a disability, it won't be an easy task. Many devices or systems are available for disabled persons to communicate with others. EEG is one of the most cost-efficient and popular methods for enabling such communication. Per R. Ameri et al., there are steps involved in the EEG-based Brain-Computer Interface (BCI) systems; these steps involve four distinct processes: first, EEG is captured by electrodes and placed on the scalp of the individual second step would be the artifacts and noise need to be removed from the raw, unfiltered signals; the third step would be the extraction steps where the desired information is extracted and in the last step would be just to recognize the class of features and conducting into effective control commands to drive the external systems or devices.

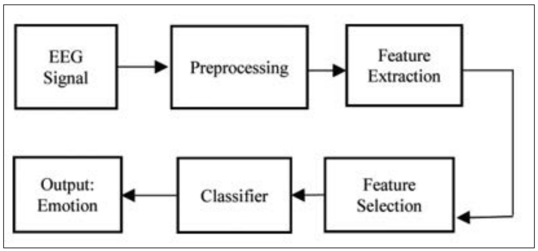
In recent years, neural networks have become a de facto tool for analyzing EEGs. A. Bertrand et al. studied the EEG channel selection in DNNS and regarded the channel selection as the grouping of neural networks in training [1]. This paper discusses the channel selection algorithms used in EEG classification in recent years. The paper's primary focus will be the selection of neural network channels and a summary of the algorithms used in the functional connectivity and statistical methods.

A wide range of BCI applications have been there for many years, but since last year, there has been activity around Generative AI where it can be utilized at its fullest potential. As BCI produces raw data along with its channels (raw waves), it would be an ideal candidate to train them to optimize the system and make it efficient.

Brain-Computer Interface

BCI uses EEG signals to communicate. EEG signals and BCI can be used to perform many activities. Such activities can be based on their usage and operational cases. For example, using the BCI based on EEG signals, a person's attention span can be detected, along with the detection of Attention Deficit Hyperactivity Disorder (ADHD), to name a few. All this data is available using the EEG and can be transferred to the computational systems using the BCI. Use cases of such things can be monitoring the driver while driving the vehicle to avoid any fatalities or anything that requires the utmost attention.

Brain waves or signals can be categorized into five categories defined based on their range: Gamma, Beta, Alpha, Theta, and Delta waves in the order of their frequency from higher to lower. Gamma waves can be detected anywhere on the skull and range between 30 and 60 Hz, which makes them the fattest of all waves. Beta waves are only present when the brain is aware, paying attention, or doing activities such as judging, decision-making, or focused activities. It ranges between 12 to 30 Hz. It is further classified into the subbands Beta1 (12-15Hz), Beta2(15-22Hz), and Beta3(22-30Hz). It also signifies that the higher the frequency score, the busier the brain. Alpha waves, the third classification, range between 8-12 Hz and mostly peak at 10Hz. It is active primarily during meditation or a peaceful state. In most cases, the tasks that require muscle memory are tracked using alpha waves. Theta waves are the fourth type and slow waves but not the slowest. They range between 4-8 Hz and are primarily present when an individual sleeps. It can also be tracked during the deep meditation stages. These waves are particularly known for intuition, learning, daydreaming, fantasizing, creativity, and memorization. These waves are primarily dependent on signals and activities when originating within. The last and fifth classification delta waves have a frequency range between 0.5-4 Hz. They are mainly observed in deep sleep. These waves are known to suspend any external signals or awareness to an individual and are a source of empathy.

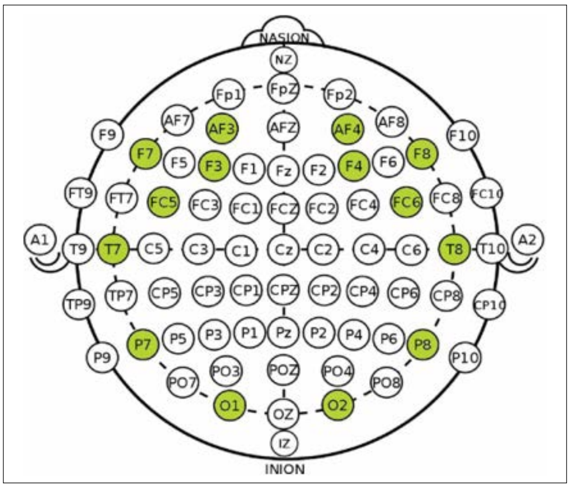


Brain waves classified earlier must be extracted pre-processed to extract the features or signals from them. It generally works collectively to generate a signal and convert it into commands. In simple terms, EEG signals must be processed in 3 stages: Pre-Processing, Feature Extraction, and Classification of these signals. In the pre-processing stage, the unwanted noise is removed. The noise in these settings is categorized into environmental and biological. Environmental noise could generate electrical signals, such as power lines, electrodes, and shielding. Biological noise can be any movement within the body, such as eye movement, heartbeats, and muscular movements. This noise must be removed before any other operations are performed on these signals. To remove the noise, various filters such as FIR (Finite Impulse Response), Adaptive, Bandpass, and other filters. These filters help to remove the noise from different types of categories of brain waves. Once pre-processed, the next step would be the feature extraction from the signal. The feature extraction is divided into three domains: time, frequency, and time-frequency domain. The data is used to perform the fast Fourier transform to convert the time domain data to frequency domain data and then calculate the relative categories of the signal. P. Santhiya et al. extracted the signal using methods defined in the feature extraction, where all the bands were calculated again in the five different frequencies [2].

After the pre-processing and feature extraction, the last step is to classify the data. There are many techniques to classify the data, such as a Support Vector Machine (SVM) is a statistical theory, Linear Discriminant Analysis for dimensionality reduction after removing dependent features from the signal, K-Nearest neighbor to find the closest object. Among all the methods, KNN has a better yield and accuracy than SVM.

Methods for Data Collection

R. S. Kumar et al. used an Epoc EEG headset to collect the data using the traditional wet electrodes [3]. They used EPOC+ 2019 to use the electrodes AF3, F7, F3, FC5, P7, O1, O2, P8, FC6, F4, F8, and AF4 to arrange them in the frontal and parietal lobes of the skull.



In the configuration, they used T7 and T8 as reference channels for the experiment. The naming would be pre-frontal (Fp), frontal (F), temporal (T), parietal (P), and occipital (O) for the reference diagram. They received an accuracy of around 80% when one electrode was increased to 97.5% when a group of electrodes were used.

Generative AI

Generative AI is based on the models used to train the data set over multiple individuals to attain accuracy. Generative AI can be used to train the models and tune the models in a way that increases the accuracy of the outcome. Using the foundation model and the tunable data sets would help decode the data generated using the feature extraction. In a real sense, this would enable persons with disability and empower them to communicate better and more efficiently. The channels are based on the neural network and take the channel inputs individually for the input as a neural network, which trains the datasets individually over the group of data sets [4]. W. Mu et al. used and referred to various methods to collect and process the data using Machine Learning and Neural Networks to increase the efficiency of the models [5].

Generative AI takes large datasets and trains them. These datasets are trained and unsupervised repeatedly to remove false positives. This training is difficult as it requires vast computing power and time. Typical training for such a model takes days and may require multiple retries before it can be right. During data collection, privacy is one of the parameters that need to be removed from the dataset, but oftentimes, it slips through the training and must be removed from the model. It can be achieved by repeatedly turning and training the model to clean the data from such artifacts of the dataset.

Conclusion

Using the BCI data collection along with the Generative AI presents a great benefit to the persons with disability. It would benefit many and help many communicate with the outside world using a dedicated device or computer. BCI can get more help and boost by utilizing the GAI on end-user devices to help individuals [6,7].

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