Development of the Electroencephalograph-based Brain Computer Interface System

Xiang Gao\textsuperscript{1, a, *, †}, Gesangzeren FNU\textsuperscript{2, b, *, †}, Xianshu Wan\textsuperscript{3, c, *, †}

\textsuperscript{1} Electrical and Information Engineering, Tianjin University, Tianjin, 300072, China
\textsuperscript{2} Department of Science, University of Wisconsin, Steven Point, Wisconsin, 54481, USA
\textsuperscript{3} Department of Engineering, McMaster University, Hamilton, Ontario, L8S4L8, Canada

*Corresponding author’s e-mail: \textsuperscript{agx31@tju.edu.cn}, \textsuperscript{bggesa432@uwsp.edu}, \textsuperscript{cwanx4@mcmaster.ca}

† These authors contributed equally.

Abstract. A practical BCI-based application design contains a variety of design stages are needed to be considered. The design challenges are majorly present in 3 major stages: brain signal acquisition, signal processing unit, and signal classification. Combinations of different approaches have to be employed to achieve the functional and accurate performance of the overall design. Those design choices, algorithms, and methodologies that are meant to solve design challenges presented in the previously mentioned three stages have become a hot subject of a number of studies. This paper aims at providing a thorough overview of existing methodologies for BCI-based application design, comparing their principles and performance and recommending suitable design choices that would yield an objective result for the application.

1. Introduction

Brain's computer interface is a technique that interprets the user’s brain activity patterns into data for the collaborative application. Through the system, brain activities could be measured and processed [1]. To measure the BCI user’s brain activity, electroencephalography is normally applied, which is called the EEG. The EEG-based BCI system could make the user control without doing any physical activity. This could revolutionize many application areas, especially could prove to control assistive technologies to the motor-impaired users. Two phases are importantly required to use a BCI system: the first one is an offline training phase. During this phase, the system is being calibrated for the user. The second one is the online operational phase. During this phase, the system can recognize brain activities’ patterns. When the BCI system gets the data, it can translate the data into messages and commends for the computer to process [2]. The online BCI system is a closed-loop, and the system starts with the user to produce a detailed EEG pattern, and after that, their EEG signals will be measured. After that, the EEG signals are pre-processed by a variety of spatial and spectral filters [3], and features are extracted from the EEG signals to correspond to the signals in a specific compact form [4]. At last, the EEG features are being classified by the algorithm [5], after the classification, the information is translated into the
command for application use [6]. The user should be informed whether their special mental command was recognized or not before their feedback is provided and returned to the application system [7].

2. Signal acquisition module

2.1. Signal acquisition BCI classification

The signal acquisition component is responsible for documenting the electrophysiological signals that provide input to the BCI. The signals are recorded from the human scalp or brain surface or neuronal activity [8].

Invasive BCI includes electrocardiograms (ECoG), single-neuron recordings [9] and multi-neuron recordings. Signals recorded from invasive implantation are less noisy and better in quality than non-invasive methods. Still, it is hard to commercialize and used in normal life. Compared with the booming development of the non-invasive BCI field, only a few universities such as the University of California, Stanford University, and Zhejiang University and a few high-tech enterprises such as Neuralink and NeuroPace have invested in the field of invasive BCI due to multiple technical and ethical restrictions. In the United States, BrainGate, as a technology company focusing on invasive brain-computer interface research, is committed to the research of brain-computer interface equipment for diseases such as stroke and frostbite. Neuralink, a brain-computer interface technology company founded by Elon Musk, has been certified by the FDA for human brain experiments. In the future, its products can treat major depression, Alzheimer's disease, and other diseases. In China, the new stroke artificial neural rehabilitation robot system designed by the Tianjin University neuro-engineering team has passed the inspection of the China Food and Drug Administration (CFDA). It has been clinically tested in many hospitals.

Non-invasive BCI includes Magnetoencephalogram (MEG), Positron Emission Tomography (PET), Functional Magnetic Resonance Imaging (fMRI), Near-Infrared Spectroscopy (NIRs) and Electroencephalogram (EEG) [10, 11]. Hans Berger first discovered EEG in 1929. EEG has a fairly short time constant and demands relatively facile and low-cost equipment. Therefore, the BCI system based on EEG has been widely used. Table 1 shows the major BCI research institutions and enterprises.

| Research Institution | High-tech Enterprise |
|----------------------|----------------------|
| Invasive BCI         | Non-invasive BCI     |

2.2. EEG signal

BCI-based EEG is broadly used as a result of its portability, low cost, and easy popularization [10]. The electrode placement is generally carried out according to the standard 10-20 system.
Figure 2 presents that the skull is separated into two hemispheres. All the odd numbers of the electrodes are on the left side, and all the even numbers are on the right hemisphere. The signals accumulated from the odd-numbered electrodes represent left motion images, while the even-numbered electrodes represent right motion.

2.2.1. EEG signal classification. According to frequency bands, EEG signals are divided into different rhythms, including Delta (δ, up to 4 Hz), Theta (θ, 4-8 Hz), Mu/alpha (μ, 8-12 Hz), Beta (β, 13-30 Hz) and Gamma (γ, above 31 Hz). According to the participant's status, EEG signals can also be divided into spontaneous EEG signals and evoked EEG signals [13, 14]. According to the participant's status, EEG signals can also be divided into spontaneous EEG signals and evoked EEG signals.

2.2.2. The evoked EEG signal. The evoked EEG signal is an event-related potential generated under external stimulus conditions. Typical signals include P300 potentials [15, 16], steady-state visual evoked potentials [17, 18], and slow cortical potentials (SCP) [19, 20].

2.2.3. The spontaneous EEG signal. The participant in the natural state generates the spontaneous EEG signal according to the specific task guidance. The typical signal is the α wave, μ and β rhythm recorded over the sensorimotor cortex [21, 22]. The use of the amplitude increment of the alpha wave can construct a switch control system for brain electrical equipment, which cannot require training for the operator. And μ rhythm and β rhythm perform well in the brain-computer interface control experiment of two-way motion and binary selection. Each EEG signal has its advantages and disadvantages. However, since the BCI system based on motor imagination performs well in the binary selection control experiment and has no need to train the users, most experiments now choose the α wave, μ, and β rhythm recorded over sensorimotor cortex to achieve better identification results [23, 24].

3. Signal Processing Module
For any practical non-invasive BCI design, the signal-to-noise ratio (SNR) of the recorded EEG signal is always a major concern. The overall task of the signal processing module is to increase the signal-to-noise ratio [25] to make the signal more recognizable to be categorized for further applications.

3.1. Signal Preprocessing
Due to the artifacts present in the recorded EEG signal from the non-invasive signal acquisition module, the signal contains reduced SNR. It cannot be directly fed into the classification for application uses.
The main objective in this preprocessing stage is to design certain filters and methodologies to increase the SNR of the signal and reduce the artifacts contained in the signal. Two of which commonly seen preprocessing categories are linear filtering and spatial filtering.

3.1.1. Linear Filtering. To eliminate noise and artifacts present in the EEG signal, a linear filtering system can be implemented to remove certain artifacts with no overlapping frequency bands with the EEG signals. The high-pass filter can remove artifacts from the eye movements, which majorly consists of low-frequency components. The low-pass filter can remove artifacts from the muscle movements, which majorly consists of the high-frequency component[26]. The combination of both filters is easy to be implemented by either using software design on the general processor or using hardware implementation, and no need to acquire the specific signal characteristics of artifacts. It is worth mentioning that the linear filtering techniques have limitations if the artifacts have the overlapped frequency bands with the desired EEG signal [26]. In this case, the linear filter implementation would fail to remove artifacts.

3.1.2. Spatial Filtering. Most recent studies regarding the preprocessing of the BCI system design mentioned the use of spatial filtering techniques, especially the Independent Component Analysis (ICA). ICA is a spatial filtering algorithm that applies statistics to separate linearly mixed sources. The algorithm is first whitening the data plots to make the variance equal on both axes in a 2-D dimension, making the data projection on each axis Gaussian. Then, it rotates the axis of the scattered data plot to minimize Gaussianity and maximize entropy on each axis so that produced output can be statistically independent [27], with an equal projection on each axis. Such that the original source can be recovered. Since the recorded EEG signal itself can be seen as a mixture of signals acquired from each electrode on the scalp, the signals from electrodes across epochs are considered a mixed matrix. This method effectively removes artifacts, especially for separating EEG from signals being contaminated by EMG.

3.2. Feature Extraction Methods

The original data sets acquired from the previous stages can be redundant and non-informative, causing great complexity while analyzing large data sets and reducing classification accuracy. The reduced set of features obtained by transforming the original data set helps to provide recognizable measurements and greatly reduce classification complexity. Three frequently used extraction approaches are discussed below.

3.2.1. FFT. The Fast Fourier Transform (FFT) algorithm converts the signal contents from the time realm to the frequency realm by doing Discrete Fourier Transform in a digital implementation. Using Welch’s method, the characteristic of filtered EEG signals can become distinguishable on the frequency domain with generated power spectrum density (PSD). The sequence of \( x_m(n) \) can be expressed as follows, with \( m \) windows with a hop size of \( R \) and window function \( w(n) \), as well as \( K \) frames of length \( M \) [28].

\[
x_m(n) = w(n)x(n + mR), \quad n = 0, 1, \ldots, M - 1, \quad m = 0, 1, \ldots, K - 1
\]

Then, squaring each individual FFT.

\[
P_{x_m^{M(\omega_k)}} = \frac{1}{M} \left| \sum_{n=0}^{N-1} x_m(n) e^{-j2\pi nk/N} \right|^2
\]

Calculating corresponding average amplitude from squared frames, normalizing it to the resulting power spectral density.

\[
S_{\hat{X}}(\omega_k) = \frac{1}{K} \sum_{m=0}^{K-1} P_{x_m^{M(\omega_k)}}
\]
The signal frequency pattern can thus be clearly identified in the frequency domain.

3.2.2. **Wavelet Transform.** Due to the limitation of the FFT coming from the time and frequency resolution dilemma, it is not the perfect solution for non-stationary EEG signals [29]. Therefore the wavelet transform (WT) can be introduced in the feature extraction. The wavelet transform offers varying window sizes for different frequency content to compensate for both time and frequency resolution. For fast-changing high-frequency content, a small window size is employed. In contrast, a long window is used for low-frequency. Making it a more suitable method for analyzing EEG triggering signals with sudden movement[30]. In the continuous wavelet transform (CWT), the EEG signal is represented by wavelets[31].

\[ X_{CWT}(a, b) = \int_{-\infty}^{\infty} x(t) \psi^*_{a,b}(t) \, dt \]  

In this case, a is the scaling(dilation) parameter, and b is the shifting(translation) parameter.

3.2.3. **Common Spatial Pattern.** Spatial filters are useful in improving the SNR in the analysis of EEG trails. Common Spatial Pattern is one of the widely used spatial filtering algorithms that employ diagonalizing the covariance matrix for both classes[32], such that the discriminability of two classes of data is maximized. The produced data classes more independent and recognizable compared to raw data. In recent studies, the effectiveness of the CSP method has been proved multiple times as the favored feature extraction method. The following table provides a brief summary of the resulting accuracy from using CSP as the feature extraction method in some recent literature.

| Paper Title | Year | Feature Extraction Techniques | Accuracy |
|-------------|------|------------------------------|----------|
| Evolving Spatial and Frequency Selection Filters for Brain-Computer Interfaces [33] | 2010 | CSP | Subject1: 77.96% Subject2: 75.11% Subject3: 57.76% |
| Increase performance of four-class classification for Motor-Imagery based Brain-Computer Interfaces [34] | 2014 | CSP | 78.82% |
| A Novel Classification Method for Motor Imagery Based on Brain-Computer Interfaces [35] | 2014 | CSP | 91.25% |
| A Multi-label Classification Method for Detection of Combined Motor Imageries [36] | 2015 | CSP | 51.67% |

The method of CSP does not come without its weakness, the method is sensitive to the operational frequency band of the waveform. And it may require a larger number of electrodes to obtain a higher number of channels for analysis, which can reduce the portability and the cost of the BCI device. Despite these limitations, it is undeniable that the CSP is still one of the most efficient and widely used feature extraction means in BCI system design.

4. **Three main types of EEG classification methods for BCI**

The classification of characteristic signals is based on the characteristics of brain electrical signals that can cause different responses to brain electrical activities according to different movements or consciousness and determine the relationship between movement or consciousness and characteristic signals. Talking about the task of the classification algorithm, it is to map the features that characterize the neuroelectric activity into a specified category to reflect the current activity pattern of the brain. Here are three main types of EEG classification methods for BCI.
4.1. Adaptive classifiers

4.1.1. Principles. The adaptive classifier is one kind of classifier whose parameters track the changes of the EEG signal over time, and track the distribution of possible changes, to remain effective for non-stationary changes of the EEG signal. The value of the weights is incrementally recalculated and modernized over time as new EEG data receive and turn out to be available [33, 34]. This makes the classifiers track feature distribution with possible changes, thereby letting the classifiers persist effective even when facing non-stationary signals.

Adaptive classifiers can use supervised adaptation, unsupervised adaptation, and semi-supervised adaptation. With the first type, the supervised adaptation, the incoming EEG signals’ true class labels are known. The classifier can be retrained with the available training data. And the newly available data can be augmented with these new labelled incoming data, or it can be merely updated based on this new data [33, 34]. When using the supervised BCI adaption, it required the user to do the guided training. Through the guided training, the users’ commands can get imposed. Thereby the corresponding EEG class labels are known for the classifiers. Since the incoming EEG data’s true labels are unknown, the supervised adaptation cannot be used with free BCI. Talking about the second type of adaption, the unsupervised adaptation. The labels of its incoming EEG data would be unknown. The unsupervised adaptation is based on the estimated label of the data class when enabling updating and retraining [35]. Like the covariance matrix is updated through the classifier model [36], the unsupervised adaptation could also be based on class-unspecific adaptation. The third type of adaptation is called semi-supervised adaptation, which is between supervised and unsupervised methods [37, 38]. At last, it adapts and retrain the classifier by using the initially unlabeled data, and assigned the data to the estimated labels.

4.1.2. Pro and Cons. Most of the current adaptive classifiers for brain computer interfaces are in line with supervised adaptive classifiers. Adaptive classifiers are better than non-adaptive classifiers for various types of BCI. Supervised adaptation is the most efficient type of adaptation since it can access the true labels. In multiple studies [39, 40], the unsupervised adaptation is superior to static classifiers [41, 42]. The unsupervised adaptation ought to be applied to reduce and even eliminate the need for calibration [43, 44]. The majority of the real BCI applications do not provide the required labels [45], therefore these BCI applications can only rely on unsupervised methods, so more robust unsupervised adaptation is needed for real use. Even though the performance of adaptive classifiers is better than static classifiers, but it is not free to use, it requires a lot of labeled data, and new input data also needs to be labeled. And for the user experience, to let the classifiers recognize the users, the user must adapt to the BCI by learning how to execute mental imagery tasks.

4.2. Transfer learning

4.2.1. Principle. Training data is used as the key to the classifier training, and test data, which is used for the classifier evaluating, belong to the same feature space. This hypothesis is often violated in some applications, such as computer vision, biomedical engineering, and brain computer interfaces. When the data are acquired from multiple subjects and spanning various time sessions, the BCI system occurs a change in the data distribution.

Transfer learning aims to process those data that violate the hypothesis. Transfer learning exploits the acquired information while exploring a given task to solve some different but related tasks. Further it is a set of methodologies aiming at enhancing the performance of one learned classifier, which has been trained on one task. And enhancing the performance based on information achieved while learning another task.

Transfer learning is significant in those circumstances where there are luxuriant labelled data for one exist given task, while there are not enough data to acquire for a second task. Indeed, in this case, transferring knowledge from the given task to the second task acts as a bias or a regularizer of solving the aimed task.
4.2.2. Pro and Cons. Transfer learning is beneficial in the subject-to-subject and session-to-session performance of decoding. This is indispensable to have the ability to achieve a true BCI model which is calibration-free of operation in the future. If this model is made, it will improve the usability and acceptance of BCI. In fact, in most of the community right now, the calibration session might be overly tiring for the clinical users. For those clinical users, the cognitive resources are limited, and the calibration is annoying and unnecessary for healthy users. For novice users, it will be highly motivating and encouraging to receive feedback from the very beginning of their BCI experiences [46]. Then, before transfer learning applies to the cooperative and adaptive strategies, it can provide the users with a well-performing BCI. Transfer learning could initialize BCI by using data from other sessions for a known user and data from other subjects for a naïve user. This initialization is suboptimal; hence this approach requires adapting the classifier during the session. Therefore, transfer learning and adaptive classifiers need to develop together to attain the final goal of having the calibration-free BCI model of operation [47]. The combination of adaptive classifier and transfer learning is the cutting-edge of the present research of BCI. It is going to receive ascending attention in the future. It leads to the new generation of the calibration-free BCI mode.

4.3. Deep learning: convolutional neural networks
In deep learning, the features and the classifiers are directly learned from raw data. The model’s architecture makes the word “deep learning”. Due to the cascade, the features are associated with the elevating levels of the concepts. We are focusing on the most popular deep learning method of BCI: CNN.

CNN is a feedforward neural network. Information flows unidirectionally from the input to the hidden layers to the output. The feedforward neural network has at least one convolutional layer [48, 49]. This convolutional layer maps the input to output through one convolution operator. ConvNets are very successful in several domain applications. The ConvNets can learn the most correlative features for the handy tasks, but the performances are consumingly dependent on the architectures and the learning hyper-parameters.

5. Conclusion
In conclusion, the paper has provided a comprehensive discussion on major findings, methodologies, and concerns in three necessary modules (signal acquisition, signal processing, and signal classification) of the electroencephalograph-based BCI design.

For the parts of the signal acquisition module and classification module, the specific advantages and limitations of methodologies were discussed, indicating that the performance of each method can be varied due to specific cases. The choice of method should be verified according to the detailed design objective. As for the signal processing module, the authors prioritized the methodologies mentioned in part, suggesting ICA and CSP as the possible optimal choices for the signal processing module. The future development of the BCI design related to electrical and computer engineering domain would be focused on the signal extraction and classification algorithm. These two stages can greatly improve the performance and extend the application of the design. The paper is intended to explore challenges present in the BCI application design related to the domain of three modules mentioned previously. With various methods listed in the paper, the path for the potential design decision can be directed.

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