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Brain-Computer Interface (BCI) In Neuroscience From 2008 To 2023: A Survey

Anqi Zhang

Xin Tian

BRAIN-COMPUTER INTERFACE (BCI) IN NEUROSCIENCE FROM 2008 TO 2023: A SURVEY

Anqi Zheng
Georgia Institute of Technology
azheng72@gatech.edu

Xin (Shirley) Tian
Kennesaw State University
xtian2@kennesaw.edu

ABSTRACT

As modern technologies have developed over recent decades, neuroscience as a field has been transformed. One of the newly emerged and developing techniques is the brain-computer interface (BCI). BCI is a direct communication pathway between the human brain's electrical activity and an external device ([1]). The application of BCI is getting popular in medical fields, entertainment, and mental state monitoring. This article performs a survey of the literature from 2008 to 2023 and presents the trends and patterns in the comprehensive use of BCI in the field of neuroscience over the past fifteen years. The article covers an investigation of spatial filtering techniques, classifications, types of bases of BCI, applications, and non-technical aspects.

Keywords

Brain-computer interface, BCI, neuroscience, special filtering, classification, EEG, motor imagery, nonmedical use

INTRODUCTION

Brain-computer technologies have been used in the medical field for several decades, following the discovery of electroencephalography (EEG) in 1929([1]). EEG signals exhibited by brain neurons are known to assist in the diagnosis of psychiatric disorders like depression and anxiety ([2]). Brain-computer interface (BCI) is a direct communication pathway between the human brain's electrical activity and an external device that widely uses technologies such as EEG ([1]). EEG-based BCI, a relatively new brain-computer application of EEG, is a communication system that extracts specific features online and automatically from EEG signals that can be detected on the scalp and uses these to operate external devices, such as computers, switches, or prostheses ([3]). Motor imagery (MI), usually EEG-based, can provide an intuitive mapping of direction between BCI interfaces and control commands better than other systems ([4]). Steady-state visual evoked potential (SSVEP)-based BCI has also gained attention among researchers in recent years ([5]). Researchers in the past fifteen years have been studying the development and applications of common types of BCIs in the medical field. For example, BCI-based therapy has shown promising results in patients with motor disabilities resulting from diseases like stroke and amyotrophic lateral sclerosis (ALS) ([6]). For patients with speech impairment, BCI could offer a future efficient means of communication by decoding the neuro signals ([7]). There are also nonmedical uses of BCI in entertainment and mental state monitoring, with the common use in game development, improving safety-critical applications such as driving, and managing task capacity in industrial applications ([8]).

The article aims to present an overview and the trends and patterns in (1) the technologies (spatial filtering, classification, data processing methods) used in the applications of BCI, (2) the global distribution, and the common conferences that accept related scientific journals. We used Georgia Tech Library as a main source for obtaining research articles. The search criteria were the keywords in our review's objectives, with the restriction of creation date: 2008 to 2023, subject: Neurosciences & Neurology, and all the journals must be peer-reviewed. Section 2 reviews the key procedure and methodologies of each article. Section 3 discusses the results of the study and presents related discussions, and section 4 concludes the paper.

METHODOLOGY

Overview

The total number of articles selected for this survey was 51, and 42 were selected for data collection. Among the nine articles being excluded from data collection, one of them was used as a reference for adaptive classification and the date was not within the target range, one is an ethics discussion, one is a literature review reference that was not related to the topic, one is a reference for BCI illiteracy, one is a summarized discussion and four of them are not suitable for collecting data.

Table 2. Details regarding the methods and data processing tools

Among the 42 articles used for data collection, we collected the following information: spatial filtering technique, method/technique used (not limited to research methods), classification, dataset, type of BCI signal base, data processing tool, country, journal/conference name, findings and abstract.

The types of articles were categorized into four categories: evaluation/analysis, method/algorithm/model, application, and review, with most articles being evaluation/analysis (47.62%) and method/algorithm/model (42.86%). Articles that investigated certain research questions were classified as "evaluation/analysis" type; Articles that proposed new methods/ algorithms/models or evaluated them were classified as "method/algorithm/model"; Articles that were specifically researching on BCI related applications were classified as "application"; And articles that are either scientific reviews or literature reviews were categorized as review.

Techniques

The type of spatial filtering technique was categorized into common spatial pattern (CSP), other, and N/A. Common spatial pattern is a supervised mathematical procedure commonly used in signal processing for separating a multivariate signal into additive subcomponents ([9],[10]). Most of the articles did not present a significant spatial filtering technique (61.90%), CSP was the most common technique (30.95%), and four articles presented other techniques (9.52%).

The type of classification was categorized into linear discriminant analysis (LDA), support vector machine (SVM), steady-state visual evoked potential (SSVEP), other, and N/A. LDA is a statistical method commonly used in statistics to separate multiple classes of objects ([11]). This technique transforms the feature vectors in different classes from high-dimensional to low-dimensional fields ([12]). SVMs are a type of supervised learning model that analyzes data for classification and regression purposes. SSVEP signals are natural responses for visual stimulations, and SSVEP-based BCIs detect the subject's selection by recognizing specific components from their EEG signals([5]). The most common classifications were LDA and SVM, with 12 articles using LDA (28.57%) and 7 using SVM (16.67%).

Data Processing

During the investigation of the articles, we noticed a common procedure for EEG data processing used in these BCI studies. The three stages are recording the EEG dataset, EEG data preprocessing, and feature extraction and classification.

A large majority of the studies we investigated collected their own dataset, others directly used data from public EEG datasets such as BCI Competition I to IV. Out of the 27 articles that recruited participants and recorded their own dataset, only 8 successfully obtained over 20 subjects (29.63%), with 4 having over 70 subjects overall (14.81%). All participants in the studies were asked to familiarize themselves with the BCI equipment and environment, then attend several sessions with normally over 20 trials as instructed.

For stage two, the EEG data is passed into a bandpass filter from 0 to 200 Hz, and some with an additional notch filter for noise filtering.

Lastly, classifiers such as CSP and LDA are trained and used to classify the EEG data from each training run. Frequency bands are also used to discriminate between the classes ([13]).

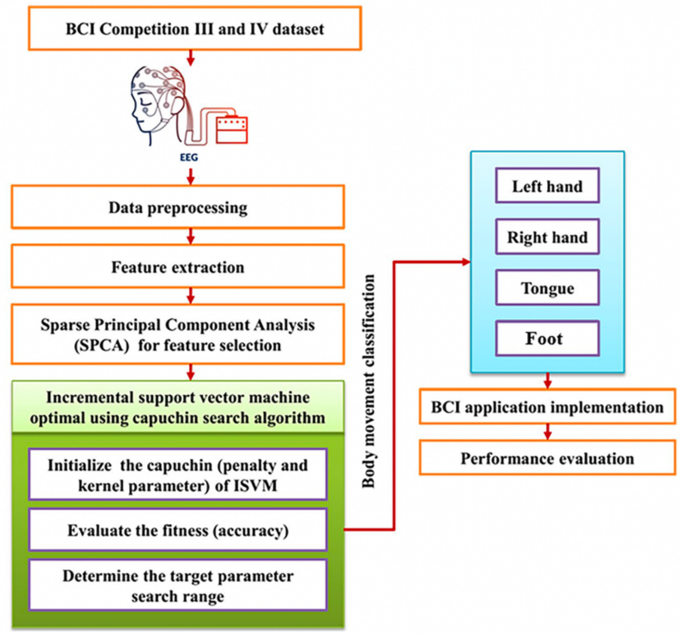

Figure 1: A proposed architecture system for BCI data processing. Adapted from "OISVM: Optimal Incremental Support Vector Machine-based EEG Classification for Brain-computer Interface Model" by P. S Thanigaivelu, S. S. Sridhar and S. Fouziya Sulthana, 2023, February 28, Cognitive Computation 15, 888–903(2023). Copyright 2023 by Cognitive Computation

Text Mining

We used MeaningCloud as our main tool for text mining. The content input for all APIs was the abstracts of all 42 articles.

Text Clustering API

Text Clustering is MeaningCloud's API tool for grouping a set of texts in a way that texts in the same group(cluster) are more similar to each other compared to other clusters (www.meaningcloud.com.). The algorithm receives a set of texts and returns a list of detected clusters. The results produced by the AI are ranked in the score it generated based on the relevance value according to its algorithm, and the result clusters are all assigned a title, a size, and a score. The titles with the highest scores are Spatial Filtering (223.18), Mental State (178.50), Artifact Removal (174.72), BCI Competition IV Datasets (168.75), and Effects of two Parameters on the ErRp (160.37).

The topics with the top sizes are BCI Performance (9), BCI Control (7), External Devices (6), Spatial Filtering (5), BCI Technology (5), and Mental Tasks (5).

Topic Extraction API

Topic Extraction is MeaningCloud's solution for extracting elements of relevant information from unstructured text such as named entities, concepts, time and money expressions, and quantity expressions (www.meaningcloud.com.).

The results of topic extraction present an entry type, a relevance score, a form (topic), and its type. The most relevant topics of the entry type Entity are Brain-Computer Interface (100), Motor Imagery (20), BCIs (17), SSVEP (17), Common Spatial Pattern (6), BCI system (6), and VR (5). The most relevant topics of the entry type Concept are brain (100), performance (61), subject (50), interface (46), methodology (42), classification (42), system (35), feedback (34), and amyotrophic lateral sclerosis (32).

RESULTS AND DISCUSSION

Results

In this section, the results of the statistical analysis are presented and discussed.

Article Category

The most common type of article according to our classification is evaluation/analysis (47.62%), followed by method/algorithm/model (42.86%), which indicates that a large proportion of the articles on BCI in neuroscience are likely to be studies that propose new methods and algorithms to assist in future studies and applications, or studies that dive deeper into current methods and techniques.

Spatial Filtering

According to our statistics, the most popular spatial filtering technique among the 42 articles is common spatial pattern (30.95%), with a few other techniques such as subject-specific spatial filters, a combination of two-dimensional spatial filters, or canonical correlation analysis (CCA) (9.52%). Only about 40% of the articles we reviewed present a significant spatial filtering technique, and CSP accounts for over 75% of these articles.

Classification

The most used classification among the articles is LDA (28.57%), showing that LDA may have an advantage when used for training datasets in BCI studies compared to other classifications such as SVM (16.67%) and SSVEP (7.14%). About half of the articles provide a clear classification method, and LDA accounts for about 56% of them.

Type of BCI

Out of the 42 articles, 20 were EEG-based BCI (47.62%), showing the popularity of EEG-BCI in non-invasive BCI studies. EEG is commonly used as a medical test to assist in the diagnosis of various brain-related diseases like seizures, Alzheimer's disease, and head injuries. EEG-BCIs allow brain-derived communication in patients with amyotrophic lateral sclerosis (ALS) and motor control restoration in patients after spinal cord injury and stroke ([3]). The second most investigated BCI base is motor imagery (26.19%). Compared to other BCI systems such as SSVEP-BCI, MI-BCI shows disadvantages overall due to higher BCI illiteracy, which is that BCI control doesn't work for a certain portion of users even after BCI training ([4], [50]). Several studies aimed to improve the performance of MI-BCI by targeting on either technological factor such as algorithm improvements, or human factors such as the factors affecting the generation of high-quality EEG patterns ([4]). Some previous studies have attempted to improve MI-BCI performance by providing visual feedback, while others tried to improve training methods or use auditory feedback ([4]).

BCI articles over the years

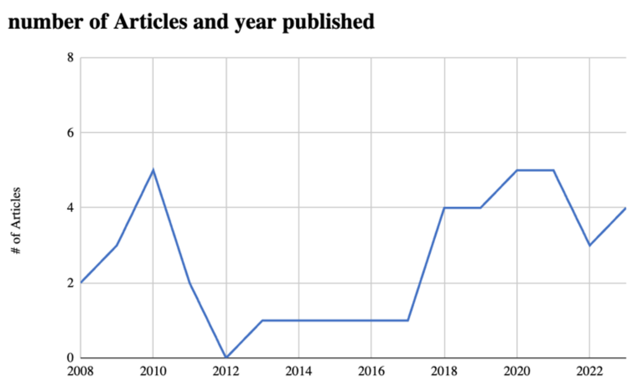

Figure 2. Number of articles and year published.

We visualized the trend of the number of articles and year published (*Figure 2*). The graph indicates two possible peaks of BCI-related studies in neuroscience: 2008 – 2010 and 2018 – 2023. The number of articles increased significantly during these two periods, with the maximum number of articles per year being 5 and 5 in 2010 and 2020. We still need to review many more articles to have a more precise view of the overall time distribution of them, but we can predict that the number of works will keep increasing soon since BCI is still a relatively new and developing field of study. As a subject that has attracted researchers' attention from all over the world, there will very possibly be groundbreaking studies in the future.

Location

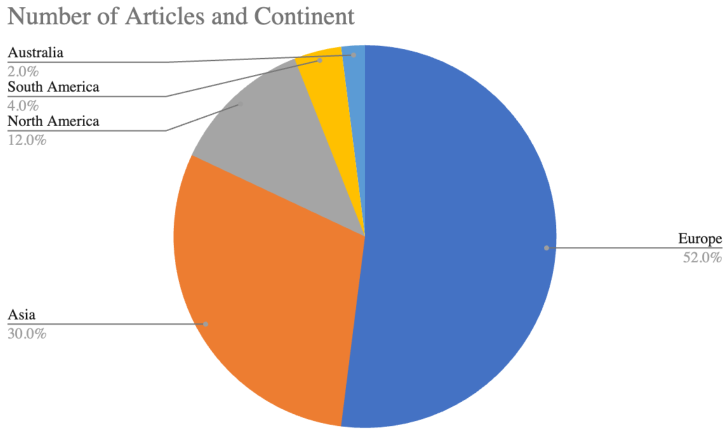

Figure 3. Number of Articles and Location

The statistics show that all the reviewed articles come from one or several of these five continents: Europe (52.0%), Asia (30.0%), North America (12.0%), South America (4.0%), and Australia (2.0%). European countries published a significant proportion of neuroscience related BCI articles, especially Germany. Out of 42 articles, 12 of them were published in Germany or had crucial researchers from Germany. The second country is China (6 out of 42), followed by the US (4 out of 42). The results are surprising to us since we originally expected that most works come from the US. We assume the reason Asian countries and European countries produce more BCI-related works than North America has to do with patient medical records reveals policies in these areas. It's possible that patients with motor disabilities and communication disabilities aren't exactly willing to share their data with researchers, and due to different patient privacy policies according to location, access to medical data may vary.

Conference

During the process of analyzing data, we noticed that some journals and conferences tend to accept neuroscience BCI articles. *Journal of Neural Engineering* and *Frontiers in human neuroscience* are the two journals that take the most articles in our survey, with each accepting 8 articles (19.05% of all articles). *IEEE Transactions* and *Frontiers in Neuroscience* are also some common journals for BCI works, with each accepting 4 articles (9.52%).

CONCLUSION

The development of BCI in the field of neuroscience has been rapid over the past 15 years. In this paper, we have reviewed 51 recent articles related to BCI and neuroscience and have collected critical information from 42 of them for our research study. Most of the articles are evaluating or proposing methods, algorithms, or models for spatial filtering techniques or classifications. The most used spatial filtering technique is CSP, and the most frequently used classification is LDA. EEG-based BCI is the most popular type of BCI regarding signal base due to its relatively low BCI illiteracy and high precision.

An interesting trend we noticed is that European and Asian countries publish more neuroscience BCI works compared to highly developed countries like the USA. Also, there are certain journals and conferences such as *Journal of Neural Engineering* and *Frontiers in human neuroscience* that prefers neuroscience BCI articles over the other journals.

This paper is still a work in progress, and we hope it will provide useful information for future researchers in this area.

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