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Brain-Machine and Python Interface

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Abstract

The joint review of the two studies addresses the use of brain-computer interfaces (BCIs) applied to people with motor disabilities or neurological diseases. The first review focuses on the use of electrocorticography (ECoG) to obtain adequate spatial and temporal resolution for communication, highlighting the preferences of people with locked-in syndrome. The second review focuses on EEG technology and programming in Python, identifying tools such as MEDUSA and BioPyC that facilitate BCI research by acquiring, processing, and presenting EEG signals. These platforms provide access to researchers with different levels of expertise and could improve the accuracy of signal classification algorithms. Both reviews underline the potential of BCIs to help people with paralysis regain motor control and improve their quality of life. In addition, the strategic importance of EEG technology in improving BCIs is highlighted, as well as the crucial role of deep learning in optimizing typing speed by implementing automatic typing of probable letters in specific contexts. Despite the advances identified, they face challenges of accuracy, accessibility, and ethical limitations, as well as the need for further research to refine the effectiveness of BCIs in real-world settings and ensure their applicability in various situations for different populations.
Key words: EEG, electroencephalogram, BCI, deep learning, artificial neural networks, Python, decoding, neurological diseases

Introduction

Brain-machine interfaces (BCI) have evolved over time, seeking to establish direct communication between the human brain and an external device, such as a computer; for this, neuronal activity is studied, allowing us to carry out daily life actions through brain signals, thus making it possible to apply them in various sectors such as health, mostly focused on prosthesis checks and neurological diseases.

FIRST REVIEW

For the development of the first review, the following search equation was implemented:

("Brain-computer interface" OR "BCI") AND ("Locked-in syndrome" OR "LIS" OR "Pseudocoma") AND ("Communication" OR "Speech" OR "Language" OR "Blinking" OR "Device") AND ("Non-invasive BCI" OR "EEG-based BCI" OR "fMRIbased BCI" OR "NIRS-based BCI")

Based on this equation, we sought to identify which techniques and technologies generated a study of brain activity, focused on people with neurological disease, in this case Locked-in Syndrome (LIS) or specifically focused on patients with motor palsy or post-coma of the central nervous system.

For our literature review, we used two databases, PubMed and Scopus, to conduct a comprehensive search. In PubMed and Scopus, we found a total of 7 relevant scientific articles in each of them, of these, 5 articles coincided.

In this paper, the authors [1] argue that no existing non-invasive recording method provides sufficient spatial and temporal resolution for use in a voice brain-machine interface. Electrocorticography (ECoG) provides adequate spatial and temporal resolution for speech brain-computer interfaces (BCIs). This method involves implanting a grid of 128-channel electrodes into the subject's brain. Through electrophysiological recordings of cortical neural activity, an audio synthesis can be generated.

However, this invasive approach has its limitations. Its use is mainly restricted to patients with locked-in syndrome who have no residual movement. This is because electrocorticography (ECoG) requires burr or craniotomy perforations to place the electrodes, which significantly limits the patient's movement.

The article Brain-Computer Interface for Communication

[2] focuses on the views of 28 Dutch people in the Netherlands who suffer from this syndrome. Several aspects were examined, including mental strategies preferred by these individuals.

The results showed that body movement attempts, such as speech and body movement, were the most preferred strategies. Participants justified that feeling that they are performing some body movement (active strategy) makes them feel more comfortable than applying a BCI control. In addition, an analysis was carried out of the residual movements that these people still had. The results indicated that:

92% and 93% retained some residual head or mouth movement.

54% and 53% retained some residual movement of the arm or hand/fingers.

46% had some movement in their leg, foot or toe.

These findings provide valuable insight into the residual preferences and capabilities of people with locked-in syndrome, which is crucial for the development of effective brain-computer interfaces.

The authors [3] discuss how BCI technology can help people with paralysis regain motor control by detecting and decoding brain signals. The article begins with a detailed explanation of the various types of paralysis and their impact on the central nervous system. Subsequently, the different BCI technologies, such as Near Infrared Spectroscopy (NIRS) and Electroencephalography (EEG), are discussed, and how they can be used to improve motor control in patients with paralysis are examined. They also explore current challenges in the development of BCI technologies for clinical use, such as the need to improve the accuracy and speed of brain signal processing. In addition, current limitations in the clinical use of BCI, such as the lack of financial accessibility for many patients, are discussed.

In summary, this article offers an in-depth look at how BCI technologies can assist people with paralysis in regaining motor control and improving their quality of life. It also highlights current and future challenges in the development and clinical use of these technologies. This article [4] focuses on the application of brain-computer interfaces (BCIs) to assess cognitive abilities in patients with consciousness disorders, especially those with minimal consciousness and incarceration syndrome. The authors argue that patients with

Brain lesions may exhibit distorted responses to auditory stimuli, which can be identified through the use of BCI. The study was conducted with a small group of patients, and the results suggest that BCI technology could have clinical applications for detecting signs of consciousness in this group of patients. Although communication through BCI may not be feasible for all patients, it is postulated that this technology could be critical for those with a conscious mind trapped in a paralyzed body. The authors also examine the limitations of the study, emphasizing the need to further adapt BCI technology to post-coma patients with disorders of consciousness, and consider the possibility that the questions asked of patients are too difficult or asked at times when patients were not conscious.

This study [5] describes in detail how the fMRI-based spelling device works in real time. The authors explain that the technique is based on the identification of specific patterns of brain activity associated with the mental imagination of different letters of the alphabet. These patterns are used to encode the letters and translate them into unique, differentiable fMRI signals. Automated decoding of fMRI signals enables bidirectional communication between patient and researcher, making motor-independent communication possible for people with severe neuromuscular conditions.

The article also highlights the potential clinical benefits of the device, including its ability to establish short-term communication with patients who are non-responsive and severely affected by neuromuscular disorders. In addition, the authors note that the device is easy to use and requires little prior training, making it immediately operational. However, some limitations and challenges associated with using the device in real-world clinical settings are also discussed, such as the need to adjust decoding procedures for each patient individually

This article [6] focuses on optimizing text typing speed for people with severe physical disabilities through the use of brain-computer interfaces (BCIs). The proposed system employs the detection of event-related potentials (ERP) evoked by the user's attention to a quick sequence of individual symbols on a screen. Using a language model and a classifier, the system selects the letters that the user wants to type. The study reveals that the proposed method, which considers all previous user observations when selecting letters to write, results in a 20% increase in simulated typing speed under various realistic conditions and stimuli. In addition, a technique for automatic typing of probable letters in specific contexts is introduced, contributing to higher typing speed under the new approach. The article also addresses the challenges associated with detecting events from EEG signals and describes how current systems address these challenges. Additionally, methods used to improve the accuracy of the BCI system are discussed, such as repeated observations of the brain signal and the implementation of an a priori language model, which is a statistical model used to improve the accuracy of BCI systems.

This article [7] presents a comprehensive review of the scientific literature focusing on the decoding of imagined speech using EEG signals. The authors begin by addressing both the technical and scientific challenges associated with this task, which include the low signal-to-noise ratio of EEG signals, inter-individual variability, and the need for personalized training. Various techniques and algorithms used for EEG-based decoding of imagined speech are then examined. These techniques include the analysis of specific characteristics of EEG signals, such as spectral power analysis and coherence analysis, as well as machine learning approaches, such as LDA, SVM, RF, and kNN. In addition, generative models such as HMM and GAN are explored. The authors also review recent studies that have applied these techniques to decode different aspects of imagined speech, such as individual phonemes or whole words. The article is not only limited to the review of methods and techniques, but also addresses additional challenges associated with the decoding of imagined speech in real-time and in uncontrolled environments. This review provides a comprehensive and up-to-date overview of developments in this field, highlighting both achievements and areas requiring further research.

SECOND REVISION

For the development of the second review, the following search equation was implemented (EEG OR electroencephalogram) AND (Python OR machine learning OR deep learning OR Artificial Neural Networks) AND (BCI OR Brain Computer Interface) AND (programming). The idea proposed for this second review is to identify which tools through EGG are used for BCIs, in this case focused on the Python programming language,[8] due to the fact that it simplifies the development of complex programs at the expense of an affordable reduction in performance. This is especially important in research settings.

In this second literature review, we used the same databases, PubMed and Scopus; In which a delimitation was made where the articles published from 2019 to 2023 will be addressed, In PubMed, a total of 52 articles were identified, while in Scopus 26 were found. Three articles were selected from each database for analysis.

The article [8] discusses the challenges and barriers in the field of neurotechnologies, including the need for more efficient and user-friendly software tools for brain-computer interface (BCI) research. The authors note that current platforms have limitations in terms of functionality and flexibility to meet the needs of researchers, who often need to implement new experimentation configurations. This can make it difficult to conduct experiments that require complex software, such as BCI or cognitive neuroscience experiments.

To this end, the authors present MEDUSA as a solution to these challenges. MEDUSA is a Python-based software ecosystem that provides a comprehensive and flexible platform for BCI and cognitive neuroscience research. It includes tools for acquiring, processing, and submitting signal feedback, as well as an easy-to-use interface that can be customized to meet the needs of individual researchers. MEDUSA is designed to be accessible to researchers with varying levels of BCI programming and research experience, and can be used for a wide range of applications, including motor rehabilitation, communication, and play.

The article acknowledges that there are still open questions and challenges in the field of neurotechnologies. For example, the authors note that more accurate and reliable signal processing algorithms are needed, as well as more advanced BCI applications that can be used in real-world environments. In addition, there are ethical implications to consider when using neuro technologies in various contexts, such as privacy concerns and the potential for misuse. They also suggest that MEDUSA can help address some of these challenges by providing a platform for collaborative research and development in this field.

The article [9] emphasizes some of the existing BCI toolboxes focused mainly on EEG, which lack comprehensive processing tools for other types of biological signals, in addition, the authors acknowledge that many researchers coming from various fields such as cognitive sciences, neuroscience or psychology, focused on the study of BCIs and physiological computation, They have limited or no training in programming, signal processing, and machine learning. This lack of experience can hinder their ability to study and compare algorithms effectively.

To remedy these limitations, the authors developed as an open-access platform, BioPyC, an open-source Python toolbox for offline processing and classification of EEG signals and biosignals. It aims to make BCI research more accessible and inclusive for researchers with such limitations, enabling them to conduct the study of BCI comparison algorithms. This software consists of four main modules:

Data I/O: Allows you to read different data formats from neurophysiological signals.

Signal Processing: Provides filtering and visualization of EEG signals and biosignals.

Classification: Allows the classification of signals using machine learning algorithms.

Results Display: Provides visualizations and statistical testing of the ranking results.

BioPyc is powered by Python and features an intuitive graphical user interface (GUI) based on Jupyter. It allows the processing and classification of EEG and other biological signals, such as electrodermal activity (EDA), electrocardiographic (ECG) signals, and respiration. The toolbox is designed to facilitate the standard steps of the BCI process, including preprocessing the data, extracting features, classifying, and analyzing the results. It also supports the integration of pre-processed data from other sources and provides automatic visualization and statistical testing functions. Last but not least, this software is compatible with existing operating systems (Windows, Linux, and Mac. OS) providing greater inclusivity for researchers [9]

On the other hand, based on the discussion of the article, it is recognized that during the research some limitations were addressed in terms of the comparison of customized algorithms by BCI researchers, considering that the BioPyC toolbox available for its development is still intended for a modest amount of study, supporting only a small number of BCIs. however, it is still under constant development to increase the toolbox. They also highlight the need to improve the processing and classification of electroencephalographic and biological signals, and indicate that accurate comparison of algorithms can pose problems due to variations in signal quality and noise, taking into account that BCIs are sensitive to noise, being the key unbalancer of the BCI approach based on the tests carried out in an environment given the conditions to which they would be subjected.

It is worth mentioning that BioPyC, compared to other existing toolboxes based on Python, stands out for allowing the study and comparison of physiological signal classification algorithms.

The article [10] focuses on the use of brain-computer interfaces (BCIs) for control, particularly for people who have lost mobility or control over their limbs. The problem addressed is that the performance of the algorithms used for the decoding of EEG signals has been limited, which has prevented the effective use of BCIs for control.

To address this problem, the authors propose a solution to improve classification accuracy by extracting temporal and spectral features from EEG signals and using deep learning neural networks to classify those features. The algorithm

Motion prediction uses the backward sequential selection technique to jointly choose temporal and spectral features and a radial-based function neural network for classification. The method shows an average performance increase of 3.50% compared to reference algorithms. In addition, the proposed algorithm achieves an accuracy of 90.08% in the first dataset and 88.74% in the second dataset, compared to a baseline average of 79.99% and 82.01%, respectively.

However, the authors also discuss the challenges and limitations associated with the use of BCIs for control. It is suggested that the use of multi-modality features in conjunction with a neural network classification protocol is likely to increase the performance of BCIs on various tasks. In addition, further research is needed to determine whether feature selection followed by independent classification is the best strategy and to address the challenges and limitations associated with the use of BCIs for control, such as inter-individual variability and long-term adaptation. Overall, the article provides valuable information on the use of BCIs to improve the quality of life of people with disabilities, but more research is needed to improve the efficacy and applicability of BCIs in control.

The research conducted in the article [11] focuses on the development of a novel method for robust asynchronous control of brain-computer interfaces based on Event-Related Potential Responses (ERP). The authors present the use of a deep convolutional neural network called "EEG Inception," specifically designed to process EEG signals and detect ERP.

One of the authors' fundamental contributions is their training strategy based on transfer learning between subjects and fine-tuning. This strategy considerably decreases the time required for calibration compared to previous research. During the training process, they employed a dataset of 22 subjects and EEG signals recorded while performing a character-selection task.

These EEG signals were used to train the EEG Inception network, which processes the input signal on multiple timescales, increasing its adaptability for various tasks. This innovative approach focuses on providing robust asynchronous control for ERP-based spelling systems, paying attention to various patterns related to the operation of such systems, such as Steady-State Visual Evoked Potentials (SSVEPs) and measurable differences in EEG complexity, which are related to the user's activity during concentration.

The results obtained demonstrate significantly higher performance compared to previous research, opening the door to more practical applications of ERP-based spelling interfaces. No

However, it is important to consider the limitations of the study, such as the relatively small size of the dataset and the lack of evaluation in real-world settings.

The authors' proposal entails the development of an innovative method that employs deep learning to address the challenges associated with asynchronous control of brain-computer interfaces. Its main objective is to enable the implementation of these systems outside the laboratory, thus expanding their applications in everyday life. The authors' discovery of the potential of deep learning to overcome the limitations of previous strategies based on manual features is an outstanding contribution to the field of brain-computer interface research.

At the close of this research, the authors acknowledge several limitations that must be considered. For example, they did not test the designed spelling system with users who have motor disabilities, who are the target audience for these systems. Also highlighted as areas for future research is the need for broader validation of the proposed approach in real-life settings and the evaluation of its performance in a variety of contexts and populations. These limitations could be addressed through further research that validates and refines the proposed approach in various contexts and with different user groups. It is also suggested to conduct experiments in real-world environments with real applications and users.

The article [12] addresses the problem of identifying emotional states through interaction with virtual environments using EEG signals. Identifying emotional states is important for a variety of fields, including psychology and brain-computer interfaces. However, accurate identification of these emotional states can be difficult due to the complexity of EEG signals and the variability in individuals' emotional response. To address this problem, the study uses a variety of virtual situations in virtual reality devices to investigate the influence of virtual content on neural state variation. In addition, three machine learning classification algorithms are applied to identify the emotional states evoked by virtual content.

The results of the study indicate that interaction with virtual environments can evoke different emotional states, and that these states can be accurately identified using EEG signals. In addition, it was found that certain aspects of virtual content, such as the presence of threatening objects, can have a significant impact on neural state variation. Despite the promising results, there are still open questions and aspects to be resolved. For example, a limited number of machine learning classification algorithms were used. Although the XGBoost algorithm was found to show the best ranking performance, more are needed research to determine if other algorithms might be more effective in different situations.

Overall, although this study presents an interesting approach to the identification of emotional states through interaction with virtual environments using EEG signals, there are some limitations that need to be considered. More research is needed to improve the accuracy and generalizability of the results, and to explore how different individuals respond to different aspects of virtual content.

Within the framework of the study of the article [13], three experiments were carried out with the purpose of evaluating the effectiveness of a brain-computer interface (BCI) architecture in the control of robots using EEG signals. To achieve this goal, Epoc+ electroencephalography (EEG) devices were used to record brain signals from a group of participants. These devices, equipped with 14 EEG sensors and 2 reference sensors, were placed in the subjects' heads in order to measure brain signals with high signal quality and ease of use, crucial aspects for the development of the experiments.

In Experiment 1, a classification model based on the Support Vector Classification (SVM) algorithm and a multilayer perceptron model (MLP) recognized as a more accurate convolutional neural network model was developed for the process of classifying EEG signals related to flickers from 10 subjects, who were instructed to perform blinks every 5 seconds. The authors used this public dataset called BCI Competition IV 2a, which contains EEG signals from the 9 subjects as they perform different types of hand movements and their imagination. The results obtained, with an average accuracy of 56.83% for motor execution and 51.01% for motor imagination, reflect the effectiveness of these models in the proposed task.

In Experiment 2, which involved transitioning to drone control, the SVM-based classification model and the multilayer perceptron (MLP) model continued to be used as well as the same participants as in Experiment 1. The successful application of these models resulted in an accuracy of 94.44%, demonstrating the adaptability and consistent performance of BCI in different contexts studying the feasibility of these artificial neural networks compared to previous studies that used the same dataset.

In Experiment 3, focused on the real-time control of a hexapod robot, the implementation of the classification model based on the SVM algorithm and the multilayer perceptron model (MLP) used in the previous experiments was maintained. On the other hand, the specific numbers of the model's efficiency metrics, including the rate of true positives (TPR) and positive predictive value (PPV), were a key point in the study of this experiment that indicates a successful development and application in a real-time environment. This is in order to correctly detect positive instances and the accuracy of the model's positive predictions.

In each of these experiments, Epoc+ devices were used to capture EEG signals, and the importance of processing tools and filters, such as OpenViBE 2.2.0, Hamming window filters and notch filters to eliminate external noise filtering, as well as the multilayer perceptron model (MLP) was highlighted. who played an essential role in ensuring the quality of the signals and the precise control of the robots. The importance of these devices and tools for their ease of use was underlined, which contributed to the success of the experiments.

The authors present encouraging findings on the ability of the BCI architecture to identify and categorize EEG signals with remarkable accuracy. Experiments two and three highlight the feasibility of using blink detection to control robots using brain signals. However, it is important to recognize that the accuracy of EEG signal detection and classification can be affected by external factors such as fatigue, distraction, and individual variations. The authors emphasize the need for future research to adapt BCI to more challenging environments, evaluate it in subjects with motor or cognitive disabilities, and consider safety and privacy in medical applications and real-world settings. In summary, this study highlights the potential of the proposed BCI architecture and the importance of continuous research and improvements.

The purpose of this article [14] is to empirically compare different deep learning methods for the decoding of EEG signals, with the aim of evaluating their effectiveness in the extraction of features and classification of brain signals for application in brain-machine interface (BCI) systems.

Several deep learning methods were implemented, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and short- and long-term memory neural networks (LSTMs). These methods were applied to feature extraction and classification of EEG signals in two different datasets.

The results showed that the combination of feature extraction and classification achieved better performance in the models. The importance of hyperparameter selection and data preprocessing to optimize decoder performance was highlighted. LSTM neural networks showed promise due to their ability to handle the temporality of data. The EEGNet-LSTM neural decoder performed satisfactorily in the two datasets analyzed, indicating its potential replicability and ability to maintain a high success rate in both simple and complex motor imaging problems.

However, limitations were identified, such as the exclusion of a subject in the first dataset due to the lack of adequate recording of EOG signals. In addition, the results

The promising findings should be interpreted with caution, as the study focused on specific motor imaging tasks, so it is necessary to evaluate replicability in other contexts.

The article [15] focuses on research that seeks to develop a brain-computer interface (BCI) system capable of accurately interpreting and classifying brain signals associated with imagining motor movements, specifically finger and tongue movements.

The research methodology comprises several stages. First, brain signals are recorded using an ECoG grid electrode located in the right motor cortex. Subsequently, CSP spatial filters are applied to the ECoG data using the BCPy2000 tool to write BCI2000 modules in Python. Finally, an LDA classifier, implemented in the Scikit-learn tool, is used to predict brain activity associated with movement imagination.

The results obtained indicate that the proposed system achieves an accuracy of 94% in the classification of brain activity related to the imagination of finger and tongue movements. This accuracy is significantly higher than expected by chance (50%) and comparable to the results obtained in previous BCI competitions. However, the research has certain limitations. Data were collected from a single subject, which limits the generalizability of the results to a wider population. In addition, the developed system was evaluated in a controlled laboratory environment, which could affect its performance in real-world environments. These factors should be taken into account when considering the implications of the research findings.

Conclusion

In conclusion, the following highlights of this review are derived. First, it is clear that there are not enough participants or data to accurately measure the effectiveness of electroencephalography (EEG)-based brain-machine interfaces. This finding highlights the critical need to support more research initiatives and encourage collaboration among researchers to collect more comprehensive data with the goal of improving the accuracy of those interfaces. Second, it underlines the critical importance of developing more accessible and user-friendly tools. This would not only facilitate the participation of a wider number of researchers in this field, but would also accelerate progress in research into brain-machine interfaces, resulting in a substantial improvement in the efficiency of these technologies. Finally, the need to improve the usability and convenience of EEG devices is urgently highlighted. This approach, focused on improving the user experience and reducing associated fatigue, plays a critical role in promoting the acceptance and adoption of brain-machine interfaces by patients, with a consequent positive influence on their quality of life.

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