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A Systematic Investigation Based on BCI and EEG Implemented using Machine Learning Algorithms

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ABSTRACT

BCI is a strong tool that improves human-system communication. It improves the brain's ability to interact with its surroundings. Recent decades have seen substantial advances in neuroscience and computer science. This has made BCI a leader in computational neuroscience and intelligence research. Recent technological advances including wearable sensing devices, real-time data streaming, machine learning, and deep learning have raised the need for electroencephalographic (EEG)-based brain-computer interface (BCI) in clinical and translational applications. EEG-based Brain-Computer Interfaces (BCIs) detect cognitive state variations throughout laborious tasks, making them advantageous for individuals. To fill in the gaps in the wide overview of the past five years (2019-2024), we surveyed the newest research on EEG signal detection and computational intelligence in brain-computer interfaces. To provide a more accurate account, we will begin by reviewing Brain-Computer Interface (BCI) technology and its main challenges. Modern signal detection and enhancement techniques for EEG signal collection and refinement follow. We also provide advanced computational intelligence methods for tracking, maintaining, and monitoring human cognitive and operational performance in everyday applications. Combinations, interpretable fuzzy models, transfer learning, and deep learning are used. We conclude with a sample of cutting-edge BCI-driven healthcare applications and explore future EEG-based BCI research.

Introduction

During the 1970s, studies on brain-computer interface (BCI) were first published, focusing on an alternative method of communication that does not rely on the brain's usual peripheral nerve and muscle output channels [1]. To achieve control over a prosthetic limb and execute a specific action, an initial concept of Brain-Computer Interface (BCI) proposed the identification and interpretation of brainwave signals [2]. The term "BCI" is formally defined as a direct communication channel between the human brain and an external device [3][4]. In the past decade, there has been significant attention towards human brain-computer interfaces (BCIs).

Human BCI devices of a similar nature utilize brain activity to convert human cognitive patterns. It utilizes recorded brain activity to interact with a computer and control external items or situations, such as operating a wheelchair or robot, in a manner that aligns with human intentions. Brain-computer interfaces (BCIs) can be classified into two primary groups. BCI is available in two types: active and reactive. The active Brain-Computer Interface (BCI) utilizes patterns extracted from the user's brain activity, which are directly and consciously controlled by the user, independent of external factors [5].

The user manipulates the reactive BCI's derived outputs, which are generated from brain activity in reaction to external stimuli, in order to control an application. Passive BCI is a type of BCI that examines a user's perception, consciousness, and cognitive abilities without the intention of enabling voluntary control. The objective of this is to enhance the implicit information in human-computer interaction (HCI) [6]. Instructions for conducting BCI (Brain-Computer Interface) research. In this discussion, we will explore the most prominent applications of Brain-Computer Interfaces (BCIs) that have undergone considerable research and practical implementation. (1) BCI is recognized as an approach that utilizes inherent human cognitive processes to facilitate simpler interactions [7].

Due to the lack of widespread adoption of other designs and the limitations of existing HCI approaches that are restricted to manual interfaces, BCIs have the capacity to completely transform and popularize HCIs for many applications, such as computer-aided design (CAD) and challenging operational situations [8–9]. BCIs are also being extensively researched in the fields of entertainment and health. This research aims to employ BCIs to monitor user states for intelligent assistive devices [10]. (2) Another prevalent application of BCI technology is its utilization in gaming controllers for leisure purposes. BCI devices with low cost, portability, and easy setup can be widely used in entertainment communities. Small, wireless BCI headsets that are lightweight, portable, and easy to set up were developed in the gaming sector. Although not as precise as other brain-computer interface (BCI) devices utilized in the medical domain, game developers can nevertheless utilize them, and they have been effectively promoted for the entertainment industry.

To enhance the utility of entertainment applications, certain models [11] are integrated with sensors to detect additional signals such as facial emotions. (3) The utilization of brain-computer interfaces (BCIs) has significantly enhanced the study of computational expert knowledge and neurocomputing in the fields of pattern recognition and machine learning on brain signals. Recent studies have shown that network neuroscience approaches can be used to measure the reconfiguration of brain networks that occur as a result of different types of human learning [12] - [14].

The results of these experiments indicate the potential for improving adaptive BCI architectures and uncovering the neural foundations and possible breakthroughs in BCI learning. (4) Brainwave headsets have been utilized in the medical domain to assist individuals with profound disability in efficiently operating robots using little motions such as blinking and neck movement [15][16]. Additionally, these headsets have the capability to gather expressive data using the software development kit provided by the company.

BCI has also been employed to assist individuals with recovering control of equipment and communication in situations when they have experienced muscle atrophy. BCI spelling devices have been extensively researched and are used in therapy. One well-known example of such a device is a P300-based speller. The utilization of the BCI platform [17] for the development of the BCI speller, which is an extension of the speller, has demonstrated encouraging outcomes in motivating inexperienced users to utilize this brain-controlled spelling tool.

Needless to say, there are research studies involving in combination of BCI technology as well as other ECG applications within sports science fields other than general single-based applications of EEG or BCI [18]. Overall, Brain-Computer Interfaces (BCIs) have demonstrated advantages in multiple scientific fields. As indicated, our endeavors encompass various areas of entertainment, including game interaction, robot control, emotion identification, fatigue detection, sleep quality assessment, as well as therapeutic domains such as identifying and predicting seizures, Parkinson's disease, and Alzheimer's.

Brain Communication Interface Methods

Brain-sensing devices for brain-computer interface (BCI) can be categorized into invasive, partially invasive, and non-invasive methods. Invasive devices collect brain signals from intracortical and electrocorticometry (ECoG) electrodes, which have lower surgical risk, high Signal-to-Noise Ratio (SNR), and higher spatial resolution compared to intracortical signals of invasive devices.

EcoG has a wider bandwidth to gather significant information from functional brain areas to train a high-frequency BCI system, and high SNR signals are less prone to artifacts. However, the potential benefits of increased signal quality are neutralized by surgery risks and long-term implantation of invasive devices. Non-invasive technology, such as Functional Near-Infrared Spectroscopy (fNIRS), Functional Magnetic Resonance Imaging (fMRI), and Electroencephalography (EEG), uses external neuroimaging devices to record brain activity.

fNIRS uses near-infrared light to assess the aggregation level of oxygenated hemoglobin and deoxygenated hemoglobin, but its power limits and spatial resolution limit its use for cortical activity under 4cm in the brain. fMRI monitors brain activities by assessing changes related to blood flow in brain areas, relying on the magnetic BOLD response for higher spatial resolution and deeper areas. However, fMRI has low temporal resolutions due to blood flow speed constraints and is more prone to distortion by deoxy-Hb than Hb molecules.

Non-invasive EEG-based devices have become the most popular modality for real-world BCIs and clinical use due to their superior signal quality, reliability, and mobility compared to other imaging approaches.

EEG Signal Features and Characteristics

EEG signals, which quantify the electrical activity of the brain's outer layer with great accuracy in terms of time, have been widely employed in research on brain-computer interaction (BCI). These non-invasive methods can be implemented in portable, easily accessible headphones, gathering signals in different frequency bands that do not overlap with each other.

The temporal resolution is at a high level of milliseconds, and the risk to people is far lower compared to invasive techniques that involve exposure to high-intensity magnetic fields.Nevertheless, the constrained quantity of electrodes in EEG data leads to a diminished ability to accurately pinpoint locations but a heightened ability to precisely measure time intervals. The low signal-to-noise ratio (SNR) of EEG signals must be taken into account when using them for BCI systems. This is because both objective factors, such as external disturbances, and subjective factors, such as fatigue conditions, can introduce contamination to the signals. A study has recently been carried out to tackle this drawback. Event-related potentials (ERPs) are slight alterations in EEG signals that occur promptly following the presentation of visual or auditory stimuli. They enable the examination of a particular brain's reaction to specific events.

The potentials are categorized as Visual Evoked Potential (VEP) and Auditory Evoked Potential (AEP). In EEG-based BCI investigations, the P300 wave serves as a reliable indicator of the brain's cortical reaction to an event-related potential (ERP) in a subject being monitored. Rapid Serial Visual Presentation (RSVP) and Steady-State Visual Evoked Potentials (SSVEP) are tasks that have the potential to improve the collaboration between humans and machines in Visual Evoked Potentials (VEP) tasks. The Psychomotor Vigilance Task (PVT) is a test that assesses the speed at which individuals react to a visual stimulus. This measurement is closely related to evaluating levels of alertness, weariness, and psychomotor abilities.

Applications of Machine Learning within EEG and BCI

Machine learning is a subset of computational intelligence that relies on patterns and reasoning to perform specific tasks without explicit instructions. It is classified into supervised and unsupervised learning models, with supervised learning dividing data into training and testing sets. Supervised learning is used for classification and regression tasks, while unsupervised machine learning is used when the data used to train is neither classified nor labeled. Various models have been developed for machine learning in EEG-based BCI applications, including linear classifiers, neural networks, non-linear Bayesian classifiers, nearest neighbor classifiers, and classifier combinations. Linear classifiers classify discriminant EEG patterns using linear decision boundaries between feature vectors for each class. Neural networks assemble layered human neurons to approximate nonlinear decision boundaries, with the Multilayer Perceptron (MLP) being the most common type in BCI applications. Nonlinear Bayesian classifiers model the probability distribution of each class, and Bayes rules are used to select the class to be assigned to the EEG patterns. Nearest neighbor classifiers assign a class to the EEG patterns based on its nearest neighbor. Classifier combinations combine the outputs of multiple classifiers or train them in a way that maximizes their complementarity. Transfer learning aims to improve the performance of a learned classifier trained on one task by exploiting knowledge acquired while learning another one. It can be classified into three sub-settings: inductive transfer learning, transductive transfer learning, and unsupervised transfer learning. All learning algorithms transfer knowledge to different tasks/domains, to enhance performance and avoid negative transfers. In BCIs, discriminative and stationary information can be transferred across different domains, with the selection of which types of information to transfer based on the similarity between the target and source domains.

Domain adaptation is a technique used in Bayesian Decision-Computing (BCI) to transform data spaces for decision rule classification. Covariate shifting is another technique used in BCI, where input distributions in training and test samples differ while output values conditional distributions remain the same. Transfer learning can be applied to transfer information from tasks to tasks, subjects to subjects, and sessions to sessions. In BCI, transfer from task to task involves transferring decision rules between different tasks, which introduces new signal variations and affects error-related potential. Studies have shown that signal variations originate from task-to-tasks transfer, which substantially influences classification feature distribution and classifiers' performance.

Transfer from subject to subject can also be used in BCIs to decrease training data collecting time. The least-squares transformation (LST) method proposed by Chiang et al. has been shown to reduce the number of training templates for an SSVEP BCI. Inter- and intra-subject transfer learning is also applied to unsupervised conditions when no labeled data is available. Transfer learning in Brain-Computer Interactions (BCI) involves applying features from training modules and algorithms to different sessions of a subject in the same task. Alamgir et al. proposed a general framework for transfer learning in BCIs, considering decision boundaries as random variables. Their experiments on amyotrophic lateral sclerosis patients showed its effectiveness in learning structure. Garca-Salinas et al. proposed a method to extract codewords related to EEG signals for transfer learning. Ideally, a BCI system should be independent of any specific EEG headset, allowing users to replace or upgrade without re-calibration. Wu et al. proposed active weighted adaptation regularization (AwAR) for headset-to-headset transfer, which significantly reduces the calibration data requirement for the new headset.

Discussion, Future Works, and Results

This review examines recent advancements in EEG-based research, focusing on the development of dry sensors, wearable devices, signal enhancement tools, transfer learning, deep learning, and interpretable models for EEG-based brain-computer interfaces (BCIs). The cost-effectiveness and accessibility of EEG devices are attributed to the advancement of dry sensors, which encourage further research in improving sensor materials and prioritizing user experience.

Fiedler et al. introduced the foundation for enhanced designs of dry multipin EEG caps, examining the relationship between EEG recordings and force applied and contact pressure. Chen et al. introduced a novel type of wearable sensor made from flexible materials, designed to monitor EEG and other bio-signals, intending to improve the functionality of smart personal gadgets and e-health applications. A closed-loop (CL) brain-computer interface (BCI) technique that incorporates real-time biosignal simulation could have advantageous applications in healthcare therapy. Reinforcement learning (RL) can enhance the accuracy of training models in BCI applications, improving training efficiency and classification accuracy.

One major obstacle in EEG-based technology is the removal of artifacts. Future research focus would be integrating BCI with other technical or physiological signals to create a hybrid BCI system, aiming to enhance classification accuracy and overall outcomes. The scientific community is exploring the integration of Augmented Reality (AR) with EEG-based Brain-Computer Interface (BCI) to increase the interaction between technology and human-computer interfaces (HCI). Prior studies have used the protocol called SSVEPs in exogenous BCIs, which involves using visual stimuli from AR glasses to induce SSVEP responses. With the availability of augmented reality (AR) and commercially available non-invasive BCI devices, AR with EEG devices makes augmentation possible and successful. Recent research has demonstrated that both deep learning and classical machine learning models used in EEG-based BCIs are susceptible to adversarial attacks, necessitating the development of defensive methods against these attacks. This study provides a comprehensive overview of recent progress in EEG signal detecting and interpretable models, dominance transfer, and deep learning techniques for their use in BCI systems.

Conclusion

Brain-computer interface (BCI) is a powerful tool that enhances communication between humans and systems. It enhances the brain's capacity to engage with its environment. In recent decades, there have been significant advancements in the fields of neurology and computer science. BCI's expertise in computational neuroscience and intelligence research has positioned it as a frontrunner in the field. The emergence of new technologies such as wearable sensing devices, real-time data streaming, machine learning, and deep learning has created a demand for electroencephalographic (EEG)--based brain-computer interfaces (BCIs) in clinical and translational settings. EEG-based Brain-Computer Interfaces (BCIs) may identify changes in cognitive states during demanding tasks, which gives them a benefit for individuals. In order to supplement the existing knowledge of the previous five years (2019-2024), we conducted a survey of the latest research on the identification of EEG signals and the use of computational intelligence in brain-computer interfaces. In order to offer a more precise depiction, we will commence by examining the technology known as Brain-Computer Interface (BCI) and its primary obstacles. Presented below are contemporary methods for collecting and refining EEG signals, which involve signal detection and enhancement techniques. Our services include sophisticated computational intelligence techniques for tracking, maintaining, and monitoring human cognitive and operational performance in various everyday applications. Combinations, interpretable fuzzy models, transfer learning, and deep learning are employed. In conclusion, we present a selection of state-of-the-art healthcare applications that utilize cutting-edge brain-computer interface technology. Additionally, we delve into the realm of future research on brain-computer interfaces that are based on electroencephalography.

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