Brain computer interface: future, challenges, and potential threats

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Abstract

Brain-computer interface (BCI), an emerging technology that allows communication between brain and computer, has attracted a great deal of research in recent years. Studies have shown experimental results demonstrating that this technology can restore the capabilities of physically challenged people, hence improving the quality of their lives. In addition, BCI has demonstrated remarkable achievements in entertainment and gaming, education, marketing, automation and control, among other science and engineering fields. Notwithstanding its broad range of applications, we noted a paucity of studies that discuss the potential threats of the technology to humans. While most studies focus on the development of BCI applications, efforts should equally be invested to overcome the threats (e.g., security and privacy concerns) and make the technology useful. This work provides our opinions and hypotheses on the future of BCI in revolutionizing our experiences. Furthermore, the work introduces various threats that may negatively impact further advancement of the brain-computer interface field. We have, in addition, proposed a functional model of the BCI system that may address privacy and security issues for the networked BCI applications connected over the Internet. This study opens interesting research opportunities for early and experienced researchers.

Keywords: Brain-computer interface, brain activity, machine learning, neurological disease, signal processing, augmented reality.

1. Introduction

Naturally, humans use their peripheral nerves and muscles to interact with the outside physical environments and carry out the desired actions. This necessity and premise for survival comes with a cost for people with severe neurological diseases, including amyotrophic lateral sclerosis and brainstem stroke. These people cannot control external devices, thus requiring assistance from healthy people that may not always be available. Inspired by the challenge, scientists and researchers have developed a brain-computer interface (BCI) technology that can transform brain signals into human actions independent of the peripheral nerves or muscles.

BCI, also called brain-machine interface, provides direct communication between the brain and external devices, such as computers and robotic limbs [1–3]. Bypassing the conventional communication channels for different tasks (e.g., vision, movement, and speech), BCI links the brain's electrical activity and the external world to augment human capabilities in interacting with the physical environment [1]. BCI provides a non-muscular communication channel and facilitates acquisition, manipulation, analysis, and translation of brain signals to control external devices or applications.

Since its conception in 1973 by Vidal [4], BCI has remained an active area of research with enormous promising opportunities [5–11]. Researchers have, for instance, reported remarkable achievements demonstrating that BCI can efficiently restore capabilities of people with disabilities, such as those with schizophrenia symptoms (psychosis, emotional disturbances, and cognitive dysfunction) [12–18]. Generally, BCI opportunities can be observed in gaming and entertainment [19–21], marketing and advertisement [22], security and authentication [23], healthcare [18], and education [24–26]. Given its cross-cutting nature across many aspects of developments, BCI may remain an attractive and a competitive research area over a longer period.

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Despite the promising applications of BCI, there has been a paucity of studies on the future of this technology and its possible threats when applied to humans. The present study covers typical threat concerns, including medical safety, privacy, ethics, and security. Because the natural working principles of the brain are not comprehensively understood, researchers have been recommended to focus more on the short- and long-term impacts of BCI on the general welfare of humans. Furthermore, our study investigates the unexplored research opportunities of in the field of brain-computer interface. Scientists, engineers, and researchers may capitalize on these opportunities to develop safe BCI products that advance humanity and improve quality of our lives.

2. Components of the BCI system

The BCI system comprises three fundamental components that serve specific roles: signal acquisition, signal processing, and application (Figure 1). These components are inter-connected and work together to allow the flow of brain signals to the target BCI application (e.g., robotic arm). In particular situations, control signals from the BCI application may be sent back to the brain to stimulate some common human functionalities, such as vision and hearing.

2.1. Signal acquisition

This component comprises an electronic device with electrodes for acquiring brain signals (oscillating electrical voltages caused by biological activities of the brain) that define its neurophysiological states. Signal acquisition involves capturing of electrophysiological signals that represent specific activities of the brain (e.g., movement, speech, hearing, and vision). Most BCI systems, including the commercial ones, deal with the following electrophysiological signals: electroencephalography, brain's electrical activity measured with electrodes placed on the scalp [27, 28]; electrocorticography [29–31], electroencephalographic signals measured directly with electrodes placed on the surgically exposed cerebral cortex; local field potential [32], electric potential measured around the neuron's extracellular space; and neuronal action potential [33, 34], rapid and temporary change in the neuron's membrane potential. Before being presented to the next BCI component, the captured brain signals undergo filtering, amplification, and digitization [18]. The overall performance of the BCI system depends heavily on the quality (signal-to-noise ratio) of the acquired brain signals.

Depending on the signal acquisition method, BCI can broadly be categorized into two types: invasive (electrodes implanted under the scalp to record signals directly from the brain) and non-invasive (electrodes implanted on the scalp). Invasive BCI provides a more accurate reading of brain signals, but requires surgery; non-invasive BCI does not require surgery, but suffers from weak brain signals (poor signal-to-noise ratio) that require expensive amplification hardware and sophisticated signal processing techniques.

2.2. Signal processing

2.2.1. Feature extraction

In this stage, the BCI system extracts critical electrophysiological features from the acquired signals to define brain activities, and hence encoding of the user's intent [18]. Similar to the previous stage, feature extraction should be executed accurately, ensuring that the features reflect high correlation with the user's intent to enhance the effectiveness and performance of the BCI system. Typical BCI systems employ time-domain or frequency-domain features [35–42] that take different characteristics: amplitude or latency of event-evoked potentials (e.g., P300), frequency power spectra (e.g., sensorimotor rhythms), or neuronal firing rates [18]. Therefore, before designing the BCI system, the domain transform and characteristics of features should be established. Also, confounding artifacts contained in the features that can negatively impact the subsequent stages of the BCI system should be eliminated.

2.2.2. Feature classification

The extracted features represent brain activities intended for desired actions. The classification process helps to recognize patterns of the features corresponding to these actions. For example, we can recognize features representing an instruction for moving a robotic arm. This component is usually implemented using machine learning and classification methods [43–45].

2.2.3. Feature translation

In this signal processing stage, the classified features are translated and transformed into actual commands to operate an external device (BCI application). Examples of the outputs given after feature extraction include commands for cursor movement on the computer screen, volume control on the audio device, or text writing. One important attribute of an algorithm for feature translation is adaptability [46, 47]: ability of the translation algorithm to adaptively track changes of the features and generate an appropriate output.

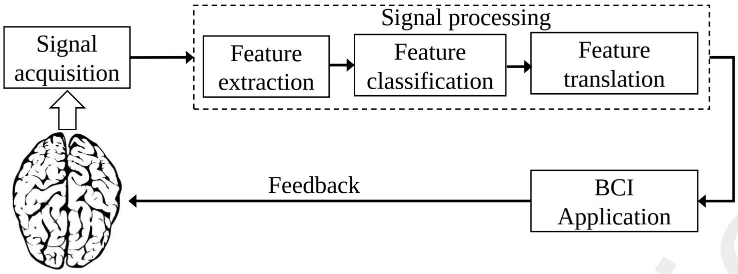

Figure 1: Main components of the brain-computer interface (BCI) system.

2.2.4. BCI Application

Feature translation generates commands that can control external devices (BCI applications): cursor [48–51] for letter and text selection on the computer screen [35, 36, 52], wheelchair [53, 54], and robotic arm [55, 56]. For BCI restoration problems, the control signals from the BCI application may be transmitted to the brain or other body organs.

3. Future of brain-computer interface

The BCI field is moving fast with a number of promising outcomes that can significantly improve human lives. Researchers require regular updates to address challenges hindering further advancement of the BCI technology. More importantly, given the multidisciplinary nature of brain-computer interface, scientists and engineers should work together to develop new and advanced BCI applications.

3.1. Decoding of thoughts

The brain, being a complex human organ, generates and controls our thoughts and other physiological parameters: emotion, touch, breathing, hearing, motor skills, hunger, temperature, memory, and anger. Some parameters, such as anger and changes of breathing rate, may be manifested outside through physical expressions or actions. However, most parameters can only be manifested internally (inside the brain) without the knowledge of other people. The current technologies cannot, for example, predict with an acceptable accuracy the thoughts of an individual. While this internalization of human thoughts—represented as brain signals in a BCI system—may have advantages, some situations may demand us to accurately decode the human thoughts. In criminology, for example, policemen would like to understand whether a suspected criminal speaks the truth. Recently, researchers have been investigating how BCI can improve the performance of polygraphs that measure the degree of truth in the arguments from a person (e.g., criminal) [2, 57–59]. Perhaps the promising results in this direction may be achieved by combining BCI and artificial intelligence techniques.

Can the BCI application facilitates translation of human thoughts accurately into a readable text? How can the accuracy of the translated text be measured? Can our imaginations be mapped into real objects, such as pictures and texts printed on a piece of paper? Can events in the dreams be accurately decoded by the BCI system to? Can we extend the applications of BCI to develop wearable devices that monitor thoughts or sleeping patterns [60–62]? Can we extract a will directly from the thoughts of a dying person? Can we print physical documents by sending command signals and data from the brain, through the BCI system, to the printer? These interesting questions need further scientific inquiry.

This study envisages that future developments of brain-computer interface will include sophisticated products that can directly map human thoughts into physical objects. We believe that, with this growing trend of BCI, people (especially those with physical disabilities) will drive and control machines (e.g., drones, vehicles, and airplanes) remotely using their thoughts [63]. The advanced developments of BCI may surface critical security and privacy issues, and hence the technology needs to be well-regulated through a universal standard [64, 65].

3.2. Extension of human memory

Stephen Hawking theorized the possibility of uploading the human mind into a computer [66]. This philosophical argument, despite its focus on the human mind (consciousness), raised a critical question on whether BCI may be a promising future technology to realize the concept. Specifically, how do we extract memory signals from the brain and decode them for storage into a computer (memory extension)? If successfully implemented, humans will be able to upload their memories into the computer for quicker processing, retrieval, transmission, and control of external devices.

In the recent developments of brain-computer interface, scientists have generated outstanding results showing that brain signals can be harvested and converted into data reflecting human intended actions. Future studies on BCI may advance these results to investigate how BCI may be used to harvest behaviors and traits from humans for research and scientific study purposes. But this inquiry should be pursued under strict ethical guidelines, a component that has not been well-captured in the BCI technology. This sensitive information, if accurately harvested, may be stored into and retrieved from the external physical memory. One may question a possible area that may apply the proposed idea. Imagine a counseling psychologist armed with accurate information on the behaviors and traits of a person. Evidently, this expert may be expected to provide a well-informed advice and conclusion, giving an appreciable impact to a person being counseled. Achieving this scientific endeavor requires an intensive multidisciplinary research.

3.3. Telepathy communication

Rao et al. demonstrated that BCI, in conjunction with the computer-brain interface (CBI) [67, 68], may allow individuals to communicate without physical interaction or sensory channels [69], a process called telepathy communication. Integration of BCI and CBI forms brain-brain interface that is still in early stages of research and development [70–73]. In future, we expect more work in this direction to expand the applications of telepathy communications in various science and engineering fields. As an example, researchers may investigate how human brains can be interconnected over the Internet of Things (IoT) network to enhance exchange of information and experiences among individuals. While few studies demonstrate the possibility of interfacing BCI and IoT [74–79], linking brains and IoT over the network remains an open-ended challenge that deserves attention of researchers. Furthermore, integration of BCI-IoT and other communication modalities, such as mind-mind interface and mind-machine interface, need further investigation to explore additional capabilities and functionalities on human-machine-human communications. All these technological advancements should, however, be made in parallel with adherence to ethical principles of humanity.

3.4. Automation and control

The promising developments in BCI suggests that the technology may be useful in automation and control industries [80–85]. Currently, BCI has received a significant deal of attention in home automation and control [86]. In this scenario, the technology assists physically challenged people to automate their daily home activities, hence making such people live independently. As the technology advances, we expect positive impacts of BCI in the industrial manufacturing processes. In essence, researchers may attempt to investigate the role of BCI in the fourth industrial revolution [87, 88]. For instance, the BCI application may be connected over a secure wireless network to automate processes in the manufacturing industry.

3.5. Intelligence sharing

Can the BCI, in conjunction with the CBI, help to reprogram the brain, hence allowing sharing of intelligence between individuals? Although it may be imagined as a fiction, the fundamental principles of the technology suggest that brains may be reprogrammed artificially. Achieving this milestone, however, requires solid understanding on the nature and functioning of our brains—a stage that has not been reached by the current state of knowledge.

3.6. Brain energy harvesting

The human brain takes only 2% of the body's mass and, for an average adult in a normal state, consumes 20% of the whole body energy budget to execute its activities [89]. This proportion of energy consumption makes it the third most energy-hungry body organ [90]. We hypothesize that the BCI technology may be combined with other advanced technologies to harvest portion of this enormous amount of energy for powering low-energy external devices. Studies are needed to realize the idea, investigating how much energy can a typical BCI system harvest from the brain.

3.7. Localized brain-computer interface

In BCI, the process of brain signals acquisition is not discriminatory. Virtually, the electrodes acquire all the available signals within the vicinity of its location (under or on the scalp). Consequently, a huge amount of signals and noise are collected for a single intended task (e.g., movement of the artificial leg), making the processing of such signals rather difficult. We can, however, tap the specific signals intended to control a targeted body part by localizing the BCI system. For example, considering a person with speech problems, the BCI system may be placed in an area that directly receives control signals from the brain. This advancement may improve the performance of the BCI system and reduce its size.

4. Challenges and threats of brain-computer interface

The BCI technology, despite its broad applications, poses threats to humans that need to be addressed. As we strive to make the technology friendly and useful, researchers should develop BCI applications that resonate with the standard principles of humanity.

4.1. Privacy

In the article by Luigi Bianchi[1], the author informs lack of specific standards that govern development of BCI applications. This challenge, as noted by Takabi et al. [91], has resulted into BCI applications with unrestricted access to brain signals. The authors' results show that these applications may, as a consequence, extract sensitive information from users without their knowledge. Therefore, to address the privacy concerns, standards should be established to define acquisition methods, access control protocols, and encryption techniques, among other attributes. Klein and Ojemann suggest that the privacy concerns and other threats may be addressed through adherence to best practices when developing BCI systems and incorporating such concerns into the informed consent protocols [92].

In this work, we have proposed a functional model of the BCI system that accounts for privacy and security issues (Figure 2). This model, which extends the work of Mason and Birch [93], contains components that may prevent unauthorized access of sensitive personal information without the user's awareness. Recalling Figure 2, before acquisition of brain signals, the BCI system engages the user with predefined access rules to ensure high integrity and privacy of information. In the signal processing block, a component "Feature selection" retains quality features intended for classification and translation. Next, for BCI applications linked with networked devices over the Internet, we propose encryption of the translated features (control commands) before transmission. This process prevents attackers from altering the control commands, a consequence that may threaten the user's safety. Other advanced technologies, including blockchain [94], may also be used to prevent unauthorized access of the control commands by the attackers. Lastly, the model contains a feature decryption block that decodes the encrypted control commands for use by the BCI applications.

4.2. Security

The field of BCI has made a significant progress in the development of medical applications and products to improve the patients' quality of life (e.g., restoration of damaged sight or hearing) [95]. However, given the increasing demand for BCI-internet communications, security concerns have emerged [96–98]. The advancement of brain-computer interface creates opportunities for cyber attackers to intervene the normal operations of the BCI application [99]. The attackers may alter commands derived from the feature translation component (Figure 1) and cause adverse effects to the target subject. Therefore, researchers should investigate security threats and vulnerable BCI components that can easily be attacked, then find robust solutions.

4.3. Safety

Safety concerns can generally be observed in invasive BCI types. Because of being implanted into the brain tissue, invasive BCI can damage nerve cells and blood vessels, hence increasing the risk of infection[2]. Additionally, the natural defence system of the body may reject the implant, treating it as a foreign entity. Another safety concern of invasive BCI is the possible formation of scar tissue after surgery, a consequence that may gradually degrade the quality of the acquired brain signals.

4.4. Ethical, legal, and social concerns

The BCI research raises a number of ethical, legal, and social concerns on privacy, security, safety, accountability, and accessibility. The society would prefer the BCI technology that addresses their questions. For example, should people be concerned on privacy and security of the BCI applications? Does the technology guarantee safety? Does the society get equal access to the technology? In a situation of negative technological or technical impacts, who will be accountable and what are the legal implications? These questions require careful considerations and further research before administering this technology to the society.

5. Conclusion

In this study, insights have been given on the future perspective of the brain-computer interface. Inspired by its benefits, the society needs to seize the available opportunities that the technology advocates. To maximize

[1] `https://lifesciences.ieee.org/lifesciences-newsletter/2019/april-2019/on-brain-computer-interface-standards/`

[2] UK Parliament POST, Brain-Computer Interface; POSTNOTE: Number 614 January 2020.

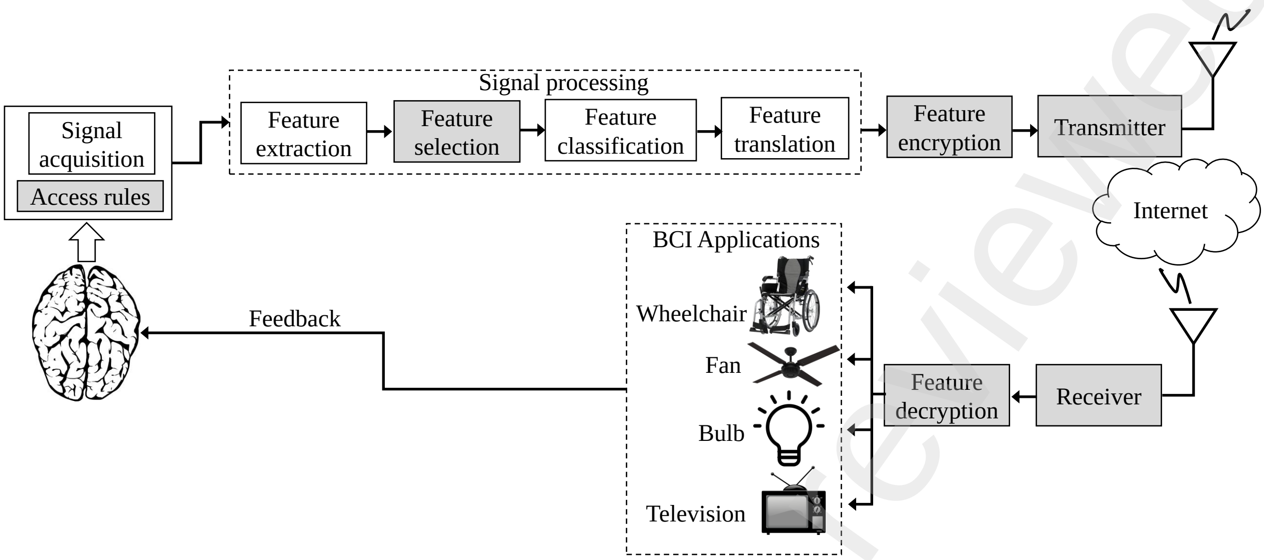

Figure 2: Brain-computer interface (BCI) system with encryption and decryption components for enhancing privacy.

the benefits and increase usability of the BCI technology across the society, researchers and scientists should address the potential threats of the technology highlighted in our work. We can fully exploit the benefits and capabilities of the technology through multidisciplinary efforts to address limitations of the current BCI systems.

In view of the BCI components, five possible research directions can be taken: cognitive psychology, medicine, biomedical electronics, signal processing, and engineering. These directions necessitate multidisciplinary research where researchers work closely to address the BCI sub-challenges. Psychologists and medical doctors should provide the fundamental working principle of the brain; scientists should develop effective signal acquisition devices along with algorithms for processing brain signals (extraction, classification, and translation of features); and engineers should develop physical BCI applications and evaluate their performance based on the predefined standards.

Conclusively, we assert that the BCI field has many research opportunities that have not been explored. From all the reviewed literature, an observation was made that the existing challenges in brain-computer interface have received little attention. The research community is recommended to address the challenges and extend the capabilities that BCI offers, including development of BCI-Internet and BCI-CBI communication devices. In addition, researchers may explore how mind-body intervention methods, such as hypnotherapy, can improve the BCI systems [100–102]. In whatever situation of development, however, the primary goal of BCI should be to advance humanity by improving the quality of people's lives.

Our future work will be focused on the middle BCI component, signal processing. Using the publicly available dataset[3,4] [103–107], we will develop computationally inexpensive algorithms for extracting, classifying, and translating features from the brain. Measures of accuracy will be established to ensure that the developed algorithms give computer commands that accurately emulate users' actions. Note that there has been no universally acceptable standard for measuring the accuracy of BCI applications, and we will attempt to narrow this research gap.

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Competing interests

The authors declare that they have no competing interests to disclose.

[3] http://www.bbci.de/competition/iii/
[4] http://bnci-horizon-2020.eu/database/data-sets

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