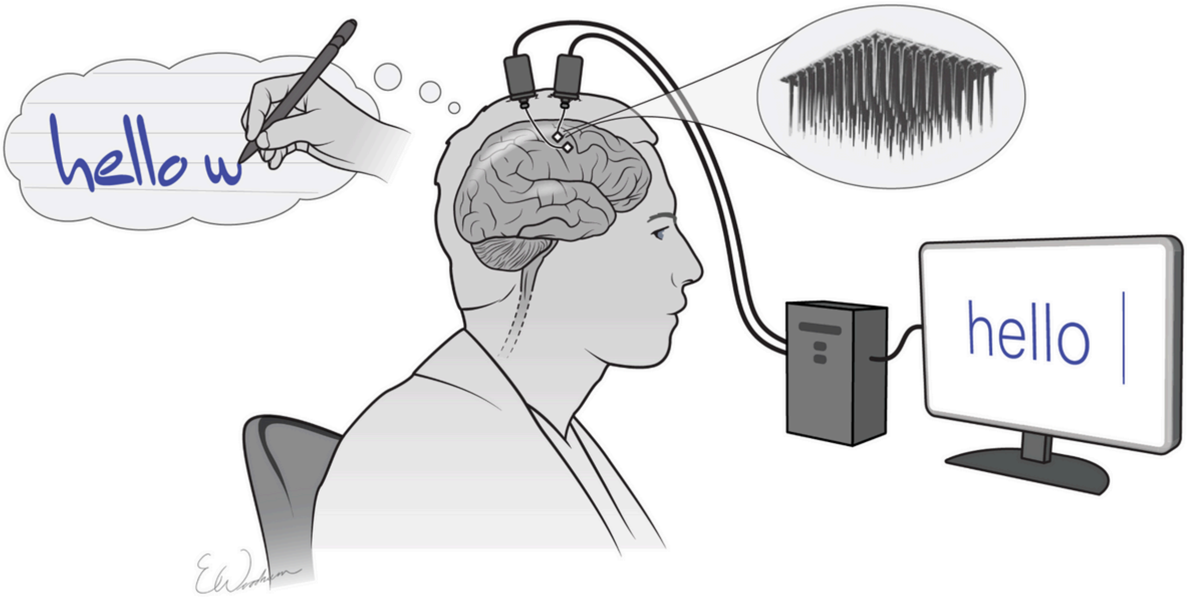
Completing The Brain

Brain-Computer Interfaces for Human Evolution and Ethical Issues



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A. Keywords

- Brain-computer interface (BCI)
- Brain-machine interface (BMI)
- Electroencephalography (EEG)
- Amyotrophic lateral sclerosis (ALS)
- Rehabilitation
- Artifact
- Neuroimaging
- Collaborative sensor system

B. Summary

A brain-computer interface (BCI) (also called brain-machine interface, BMI) is a hardware and software communications system that permits cerebral activity alone to control computers or external devices. The immediate goal of BCI research is to provide communications capabilities to severely disabled people who are totally paralyzed or 'locked in' by neurological neuromuscular disorders, such as amyotrophic lateral sclerosis, brain stem stroke, or spinal cord injury. Here, we review the state-of-the-art of BCIs, looking at the different steps that form a standard BCI: signal acquisition, preprocessing or signal enhancement, feature extraction, classification and the control interface [1].

BCIs can enable people who are paralyzed by amyotrophic lateral sclerosis (ALS), brainstem stroke, or other disorders to convey their needs and wishes to others, to operate word-processing programs or other software, or possibly to control a wheelchair or a neuroprosthesis. BCI technology might also augment rehabilitation protocols aimed at restoring useful motor function. With continued development and clinical implementation, BCIs could substantially improve the lives of those with severe disabilities [2].

C. Introduction

The human brain is claimed to be the most complicated human organ, which could be compared to a very powerful and complex computer, where, until today, no one was able to recreate and simulate successfully its entire structure [4].

A brain computer interface (BCI), also referred to as a brain machine interface (BMI), is a hardware and software communications system that enables humans to interact with their surroundings, without the involvement of peripheral nerves and muscles, by using control signals generated from electroencephalographic activity. BCI creates a new non-muscular channel for relaying a person's intentions to external devices such as computers, speech synthesizers, assistive appliances, and neural prostheses. That is particularly attractive for individuals with severe motor disabilities. Such an interface would improve their quality of life and would, at the same time, reduce the cost of intensive care [3].

BCI technology has traditionally been unattractive for serious scientific investigation. The idea of successfully deciphering thoughts or intentions by means of brain activity has often been rejected in the past as very strange and remote. Hence investigation in the field of brain activity has usually been limited to the analysis of neurological disorders in the clinic or to the exploration of brain functions in the laboratory. The BCI design was considered too complex, because of the limited resolution and reliability of information that was detectable in the brain and its high variability. Furthermore, BCI systems require real-time signal processing, and up until recently the requisite technology either did not exist or was extremely expensive [1].

D. BCI Applications

BCIs have a wide range of potential uses, from very basic to very complex. Simple applications have been demonstrated in the laboratory and in limited clinical testing. These include BCIs for answering Yes/No queries, handling environmental control (e.g., temperature, lights), operating a television, or opening and closing a hand orthosis. BCIs can also provide basic word-processing, e-mail capability, or Internet access. Such simple BCI applications can make it possible for people who lack any useful muscle control to lead lives that they find pleasant and productive. In fact, many recent studies show that, with supportive care and the capacity for basic communication, severely paralyzed people can enjoy what they consider to be a reasonable quality of life and are not much more likely to be depressed than those without physical disabilities. Thus, simple BCI applications have a viable future in their capacity to improve the lives of those most severely disabled. Indeed, a few such individuals are already using EEG-based BCIs for important purposes in their daily lives. BCIs might also control a motorized wheelchair, a robotic arm, a neuroprosthesis that provides multidimensional movement to a paralyzed limb, or other complex devices. Both invasive and noninvasive BCI systems offer the possibility of such control [2].

a. Biomedical Applications

The majority of BCI integrations and research have been focused on medical applications, with many BCIs aiming to replace or restore Central Nervous System (CNS) functioning lost with sickness or by accident. Other BCIs are more narrowly targeted. In diagnostic applications, on treatment and motor rehabilitation following CNS disease or trauma, BCIs for biological purposes are also employed in affective application domains. Biomedical technologies and applications can minimize extended periods of sickness, can provide supervision and protection by empowering persons with mobility difficulties, and can support their rehabilitation. The necessity to build accurate technology that can cope with potentially abnormal brain responses that might occur due to diseases such as brain stroke is a significant challenge in developing such platforms [5].

b. Affective Computing

Users' emotions and state of mind are observed in affective computing BCIs, with the possibility of altering their surrounding environment to improve or change that emotion. Ehrlich, S. et al. created a closed-loop system in which music is generated and then replayed to listeners based on their emotional state. Human emotional states and sensory connections can be studied with a device that is related to BCI system. Patients suffering neurological diseases also can benefit from affective computing to help them convey their feelings to others [5].

c. Gaming

BCIs focused mainly on the gaming sector have grown in importance as a research topic. However, gaming BCIs are currently a poor substitute for standard game control methods. BCI in gaming is an area where further research is needed to make games more user-friendly. In some cases, EEG data make BCI games more utilizable and increase engagement, and the system tracks each player's enthusiasm level and activates dynamic difficulty adjustment (DDA) when the players' excitement drops. When developing such systems, fine-tuning the algorithms that regulate the game's behavior is a big challenge. Some other games are based on BCI, as it is not visually intense and the graphics are not compatible with the recent generation. With setbacks, there is an engaging future for an Adaptation of P300 based Brain-Computer Interface for Gaming, which is gaining more popularity as these are very flexible to play [5].

E. How Brain Signals are Captured

a. Brain Signal Extraction

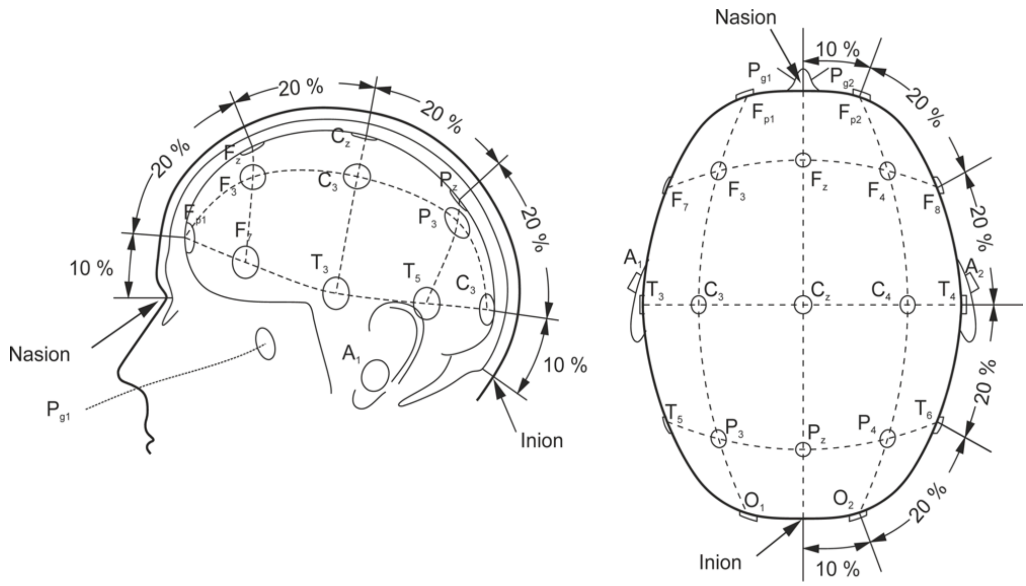
In classic BCIs, the methods used to generate brain signals can be either active or passive. To actively generate brain signals, a user can either consciously control mental activities such as motor imagery or intentionally react to stimuli from the external world (e.g., visual, auditory, somatosensory, or oddball stimuli). For example, BCI paradigms based on actively generated brain signals can allow a user to spell a word, move a cursor, and control a wheelchair or a robotic arm. In contrast, the passive generation of brain signals does not require the user to actively participate. Passive BCIs have been used to monitor users' cognitive state including drowsiness, intentions, situational interpretations, and emotional states [6].

Different techniques, which have different temporal and spatial resolutions, can be used for the acquisition of brain signals related to electrophysiology or metabolism information. Signals related to electrophysiology include electroencephalography (EEG), magnetoencephalography (MEG), electrocorticography (ECoG), local field potentials (LFP), and spike signals collected by implanted microelectrodes. The advantage of these signals is high temporal resolution. Metabolic signals can be collected by functional near-infrared spectroscopy (fNIRS), functional magnetic resonance imaging (fMRI), and positron emission tomography (PET). Among them, fMRI can provide good spatial resolution and is more sensitive to subcortical brain regions than electrophysiological signals, and therefore plays an important role in cognitive research. Importantly, electrophysiological and metabolic signals represent distinct but coupled aspects of neuronal activity [6].

By analyzing brain signals, the computer can decode the user's intention. A decoder usually consists of three procedures: signal preprocessing, feature extraction, and pattern classification. The main purpose of signal preprocessing is to remove the noise in the recorded signals to highlight the useful components. Feature extraction involves finding the feature components most related to the subject's intention. Pattern classification involves distinguishing the different intentions of users according to the extracted features. Among these procedures, pattern classification is the core algorithm in brain signal decoding. In recent years, AI and machine learning methods have been widely used in brain signal decoding [6].

b. Electrode Reference Points

The electrodes placed over the scalp are commonly based on the International 10–20 system, which has been standardized by the American Electroencephalographic Society. The 10–20 system uses two reference points in the head to define the electrode location. One of these reference points is the nasion, located at the top of the nose at the same level as the eyes. The other reference point is the inion, which is found in the bony lump at the base of the skull. The transverse and median planes divide the skull from these two points. The electrode locations are determined by marking these planes at intervals of 10% and 20% (Figure 1). The letters in each location corresponds to specific brain regions in such a way that A represents the ear lobe, C the central region, Pg the nasopharyngeal, P the parietal, F the frontal, Fp the frontal polar, and O the occipital area [1].



(A figure depicting the BCI electrode reference points on the skull) [1]

F. Detecting and avoiding artifacts

Like conventional communication and control systems, BCIs have problems with artifacts that may obscure or contaminate the signals that provide output commands. BCI artifacts may come from the environment, e.g., electromagnetic noise from power lines or appliances; from the body, e.g., muscle (electromyographic (EMG)) activity, eye movement (electrooculographic (EOG)) activity, cardiac (electrocardiographic (EKG)) activity, body movements; or from the BCI hardware (e.g., electrode/tissue interface instability, amplifier noise) or software (e.g., shadows in rereferenced EEG topographies) [7].

To avoid contamination by nonbrain signals, EEGbased BCI studies need to incorporate topographical and frequency analyses that are comprehensive enough to differentiate between EEG and nonbrain signals; fNIRS studies should incorporate analogous precautions. EEG studies that record from only one or two locations, or focus on a single narrow frequency band, cannot confidently differentiate between EEG and EMG; thus, their results can be difficult to interpret and of questionable significance [7].

G. Adapting BCIs as Brain Extensions

A BCI is a device that can decode human intent from brain activity alone to create an alternate communication channel for people with severe motor impairments. More explicitly, a BCI does not require the "brain's normal output pathways of peripheral nerves and muscles" to facilitate interaction with one's environment. A real-world example would entail a quadriplegic person controlling a cursor on a screen with signals derived from individual neurons recorded in primary motor cortex (M1) without the need for overt motor activity. It is important to emphasize this point: a true BCI creates a completely new output pathway for the brain [9].

As a new output pathway, the user must have feedback to improve how they alter their electrophysiological signals. Similar to the development of a new motor skill (for example, learning to play tennis), there must be continuous alteration of a person's neuronal output. The output should be matched against feedback from the intended actions such that the person's output (swinging a tennis racket or altering a brain signal) can be tuned to optimize his or her performance toward the intended goal (getting the ball over the net or moving a cursor toward a target). Thus, the brain must change its signals to improve performance, but the BCI may also be able to adapt to the changing milieu of the user's brain to further optimize functioning. This dual adaptation requires a certain level of training and a learning curve—both for the user and the computer. The better the computer and the user are able to adapt, the shorter the training required for control [9].

H. BCIs and Virtual Reality

Because BCI are a closed-loop systems, feedback is an important component. Various methods of providing feedback can inform the participant about success or failure of an intended act. Thus, feedback either supports reinforcement during the learning/training process or in controlling the application. In particular, the use of virtual reality (VR) has been proven to be an interesting and promising way to realize such feedback [10].

Several prototypes have enabled users to navigate in virtual scenes solely by means of their oscillatory cerebral activity, recorded on the scalp via EEG electrodes. Healthy participants were exploring virtual spaces, were manipulating virtual objects, and a spinal-cord injured patient was controlling a wheelchair through a virtual street. Additionally, evoked potentials have been used to control VR feedback as well. In these studies, BCI users who use immersive Virtual Environments (VEs) make fewer errors, report that BCIs are easier to learn, and state that they enjoy using BCIs more [10].

I. Ethical Issues

As emotions play a vital part in people's lives and are a crucial aspect of what it means to be human, the ethical implications of these developments should be reflected. Of course, not all of the ethical issues that arise in connection with BCIs are completely new. There are some ethical issues, like harm-benefit evaluations and how to deal with the collection of sensitive data, that affective BCIs share with similar neurotechnologies, particularly other types of BCIs [8].

BCIs share certain ethically relevant issues, like risks to the body, data protection and informed consent, with other neurotechnologies. BCIs can take an invasive form, where the technology is embedded in the brain. Here there is the risk of infection or brain tissue injuries. Because the avoidance of harm is a basic value in medical ethics, the well-being of the patient, the benefits of the procedure and the potential harm of the intervention need to be balanced carefully. So, similar to other invasive neurotechnologies, the ethical evaluation of benefit and harm is crucial when it comes to the use of invasive BCIs [8].

When BCIs are deployed in a medical or research context, two issues that need to be addressed are the management of expectation and informed consent. A person's self-determination is an important ethical value and a person needs to understand the potential risks of every medical intervention before consenting to the procedure. Understanding the (long-term) consequences of detecting, influencing and stimulating brain states via BCIs can be difficult and therefore, the process of informed consent requires particular attention [8].

All BCI systems collect sensitive data, which is why the issues of data security, privacy and neuro-hacking need to be addressed. This is particularly important for BCIs that collect data about mental states, as this information is highly sensitive for most individuals. Data about mental states belong to an individual's personal data and therefore need to be protected from any undue treatment by other parties. Given that BCI systems will also include elements that are not fully under the control of the user, there are some well-known concerns, like shared control and criminal guilt, that have already been addressed concerning other BCI applications. Recently, researchers have called for a veto control for semi-autonomous BCI systems. This type of veto control also seems to be something that is worth thinking about regarding BCI systems. At the very least, users of BCIs should be enabled to understand what the system does and why, and what kind of data are collected and processed [8].

J. Conclusion

The field of Brain-Computer Interfaces (BCIs) has demonstrated remarkable potential to revolutionize human interaction with technology, particularly for individuals with severe motor impairments. By leveraging advancements in signal acquisition, preprocessing, and classification, BCIs provide users with a non-muscular communication pathway, enabling them to operate devices or convey intentions despite physical limitations. Applications span diverse areas, including biomedical rehabilitation, affective computing, and gaming, underscoring the versatility of BCIs in improving quality of life and fostering independence. Despite these achievements, the field continues to face significant challenges, particularly regarding signal reliability, real-time processing, and adapting to the user's evolving needs.

Ethical considerations remain a critical aspect of BCI development. Issues such as data privacy, security, and the invasive nature of certain technologies call for stringent oversight and clear regulatory frameworks. Additionally, as BCIs progress toward broader societal integration, addressing the complexities of informed consent and managing user expectations will be paramount.

Ultimately, while the journey of BCI technology is fraught with challenges, its transformative potential signals a promising future for bridging the gap between human cognition and machine interaction.

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