A REVIEW ON INTERFACING BETWEEN BRAIN & COMPUTER-BRAIN SCIENCE

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ABSTRACT

The brain–computer interfaces (BCIs) is a relationship between human brain and machine.it has grown rapidly in the last few decades. BCIs allowing the development of ever faster and more reliable guiding technologies for converting brain activity into control signals for external devices for people with severe disabilities. In recent years, however, the scope of BCIs has been extended from assistive technologies to neuro-tools for human cognitive augmentation for everyone. A brain-computer interface (BCI), sometimes called a neural-control interface (NCI), mind-machine interface (MMI), direct neural interface (DNI), or brain-machine interface (BMI), These include new and exciting activities, such as BCIs based on the brain activity of multiple people. Due to the cortical plasticity of the brain, signals from implanted prostheses can, after adaptation, be handled by the brain like natural sensor or effector channels. Many years of animal experimentation, the first neuro prosthetic devices implanted in humans appeared in the mid-1990s. First, the review monitors a different functional brain activity such as electrical, magnetic or metabolic activity. Second, the review discusses different electrophysiological control signals that determine user intentions, which can be detected in brain activity. Third, the review includes some techniques used in the signal enhancement step to improve the performance. Fourth, the review studies some mathematic algorithms which translate the information in the control signals into commands that operate a computer or other device. Finally, the review provides an overview of various BCI applications that control a range of devices.

Keyword : - *Brain human interface, Brain computer interface, Neural interface, Brain machine interface, Augmentation of brain function etc .*

INTRODUCTION

A brain-computer interface (BCI) 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.

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. 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

BCI research is a relatively young multidisciplinary field integrating researchers from neuroscience, physiology, psychology, engineering, computer science, rehabilitation, and other technical and health-care disciplines. As a result, in spite of some notable advances, a common language has yet to emerge, and existing BCI technologies vary, which makes their comparison difficult and, in consequence, slows down the research. The community of BCI researchers has therefore stressed the need to establish a general framework for BCI design .

2.Neuroimaging Approaches in BCIs

BCIs use brain signals to gather information on user intentions. To that effect, BCIs rely on a recording stage that measures brain activity and translates the information into tractable electrical signals. Two types of brain activities may be monitored: (i) electrophysiological and (ii) hemodynamic.

Electrophysiological activity is generated by electro-chemical transmitters exchanging information between the neurons. The neurons generate ionic currents which flow within and across neuronal assemblies. The large variety of current pathways can be simplified as a dipole conducting current from a source to a sink through the dendritic trunk. These intracellular currents are known as primary currents. Conservation of electric charges means that the primary currents are enclosed by extracellular current flows, which are known as secondary currents .

Electrophysiological activity is measured by electroencephalography, electrocorticography, magnetoencephalography, and electrical signal acquisition in single neurons.

The hemodynamic response is a process in which the blood releases glucose to active neurons at a greater rate than in the area of inactive neurons. The glucose and oxygen delivered through the blood stream results in a surplus of oxyhemoglobin in the veins of the active area, and in a distinguishable change of the local ratio of oxyhemoglobin to deoxyhemoglobin . These changes can be quantified by neuroimaging methods such as functional magnetic resonance and near infrared spectroscopy. These kinds of methods are categorized as indirect, because they measure the hemodynamic response, which, in contrast to electrophysiological activity, is not directly related to neuronal activity.

Neuroimaging method	Activity measured	Direct/ Indirect Measurement	Temporal resolution	Spatial resolution	Risk	Portability
EEG	Electrical	Direct	~0.05 s	~10 mm	Non-invasive	Portable
MEG	Magnetic	Direct	~0.05 s	~5 mm	Non-invasive	Non-portable
ECoG	Electrical	Direct	~0.003 s	~1 mm	Invasive	Portable
Intracortical neuron recording	Electrical	Direct	~0.003 s	~0.5 mm (LFP) ~0.1 mm (MUA) ~0.05 mm (SUA)	Invasive	Portable
fMRI	Metabolic	Indirect	~1 s	~1 mm	Non-invasive	Non-portable
NIRS	Metabolic	Indirect	~1 s	~5 mm	Non-invasive	Portable

Table 1 Summary of neuroimaging methods

3. Electroencephalography (EEG)

EEG measures electric brain activity caused by the flow of electric currents during synaptic excitations of the dendrites in the neurons and is extremely sensitive to the effects of secondary currents . EEG signals are easily recorded in a non-invasive manner through electrodes placed on the scalp, for which that reason it is by far the most widespread recording modality. However, it provides very poor quality signals as the signals have to cross the scalp, skull, and many other layers. This means that EEG signals in the electrodes are weak, hard to acquire and of poor quality. This technique is moreover severely affected by background noise generated either inside the brain or externally over the scalp.

The EEG recording system consists of electrodes, amplifiers, A/D converter, and a recording device. The electrodes acquire the signal from the scalp, the amplifiers process the analog signal to enlarge the amplitude of the EEG signals so that the A/D converter can digitalize the signal in a more accurate way. Finally, the recording device, which may be a personal computer or similar, stores, and displays the data.

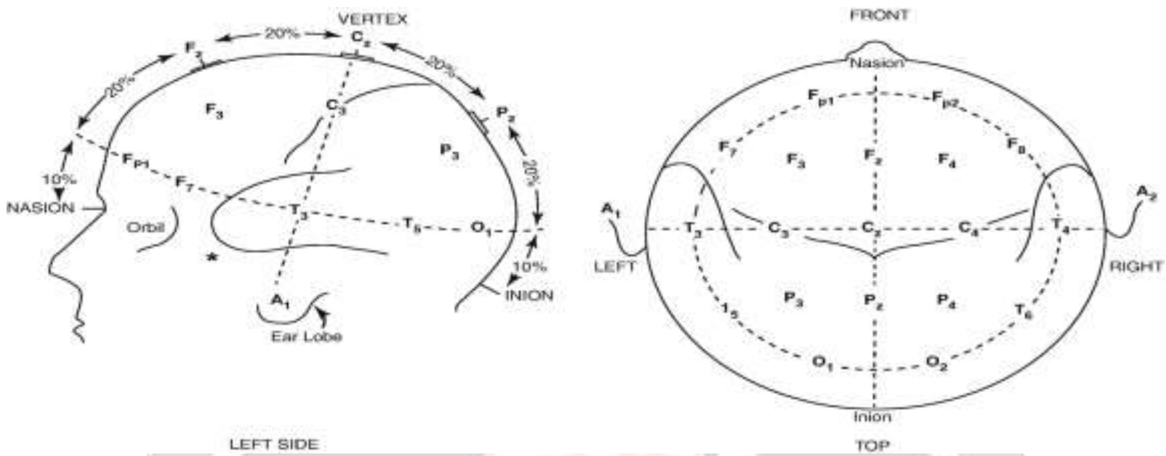

Fig 2. Electrode placement over scalp

4.Control Signal Types in BCIs

The purpose of a BCI is to interpret user intentions by means of monitoring cerebral activity. Brain signals involve numerous simultaneous phenomena related to cognitive tasks. Most of them are still incomprehensible and their origins are unknown. However, the physiological phenomena of some brain signals have been decoded in such way that people may learn to modulate them at will, to enable the BCI systems to interpret their intentions. These signals are regarded as possible control signals in BCIs. Numerous studies have described a vast group of brain signals that might serve as control signals in BCI systems. Nevertheless, only those control signals employed in current BCI systems will be discussed below: visual evoked potentials, slow cortical potentials, P300 evoked potentials, and sensorimotor rhythms. All the signal controls are listed in Table 2, along with some of their main features.

Signal	Physiological phenomena	Number of choices	Training	Information transfer rate
VEP	Brain signal modulations in the visual cortex	High	No	60–100 bits/min
SCP	Slow voltages shift in the brain signals	Low (2 or 4, very difficult)	Yes	5–12 bits/min
P300	Positive peaks due to infrequent stimulus	High	No	20–25 bits/min
Sensorimotor rhythms	Modulations in sensorimotor rhythms synchronized to motor activities	Low (2, 3, 4, 5)	Yes	3–35 bits/min

Table 2 summary of control signal

5. Types of BCIs

The BCIs can be categorized into (i) exogenous or endogenous and (ii) synchronous (cue-paced) or asynchronous (self-paced). Types of BCI are listed in Tables 3 and 4, along with information related to brain signals that can be modulated to convey information as well as advantages and disadvantages. Also, BCIs can be classified into dependent and independent . This distinction will not be detailed in this review because it is very similar to exogenous and endogenous distinction. Advantages and disadvantages in both taxonomies are analogous.

Approach	Brain signals	Advantages	Disadvantages
Exogenous BCI	- SSVEP - P300	- Minimal Training - Control signal set-up easily and quickly - High bit rate (60 bits/min)	- Permanent attention to external stimuli - May cause tiredness in some users
Endogenous BCI	- SCPs - SMRs	- Independent of any stimulation - Can be operated at free will - Suitable for cursor control applications	- Very time consuming training (months or weeks) - Not all users are able to obtain control - Multichannel EEG recordings required for good performance - Lower bit rate (20−30 bits/min)

Table 3 Main differences between exogenous and endogenous BCI

ML Approach	Advantages	Drawbacks
Synchronous BCIs	Easier control for user artifacts: user has predefined time slots to move/ blink his/her eyes Easier design (system knows at which moment of time the command from the user will be received)	Commands are imposed by the system, user cannot decide when he/ she performs an action
Asynchronous BCIs	Can be operated on free will of the user	Could be prone to the artifacts generated by the user (eye blinks and movements) Computationally more demanding as provides continuous classification in real-time

Table 4 Main differences between synchronous and asynchronous BCIs

6. Conclusions

This article has reviewed the state-of-the-art of BCI systems, discussing fundamental aspects of BCI system design. The most significant goals that have driven BCI research over the last 20 years have been presented. It has been noted that many breakthroughs were achieved in BCI research. Different neuroimaging approaches have been successfully applied in BCI: (i) EEG, which provides acceptable quality signals with high portability and is by far the most usual modality in BCI; (ii) fMRI and MEG, which are proven and effective methods for localizing active regions inside the brain; (iii) NIRS, which is a very promising neuroimaging method in BCI; and (iv) invasive modalities, which have been presented as valuable methods to provide the high quality signals required in some multidimensional control applications e.g., neuroprostheses control. A wide variety of signal features and classification algorithms have been tested in the BCI design. Although BCI research is relatively young, many advances have been achieved in a little over two decades, because many of these methods are based on previous signal processing and pattern recognition research. Many studies have demonstrated the valuable accuracy of BCIs and provided acceptable information bit rate, despite the inherent major difficulties in brain signal processing. Accordingly, user training time has been significantly reduced, which has led to more widespread BCI applications in the daily life of disabled people, such as word processing, browsers, email, wheelchair control, simple environmental control or neuroprostheses among others. In spite of the recent important advances in the BCI field, some issues still need to be solved. First, the relative advantages and disadvantages of the different signal acquisition methods are still unclear. Their clarification will require further human and animal studies. Second, invasive methods need further investigation to deal with tissue damage, risk of infection, and long-term stability concerns. Electrodes that contain neurotropic mediums that promote neuronal growth and wireless transmission of neuronal signals recorded have already been proposed. Third, the electrophysiological and metabolic signals that are best able to encode user intent should be better identified and characterized. The majority of BCI studies have treated time, frequency, and spatial dimensions of brain signals independently. These signal dimension interdependencies may lead to significant improvement in BCI performance. Fourth, information bit rate provided by current BCIs is low for effective human-machine interaction in some applications. Exogenous-based BCI may provide much higher throughput. Fifth, the unsupervised adaptation is a key challenge for BCI deployment outside the lab. Some moderately successful adaptive classification algorithms have already been proposed. And finally, most BCI applications are at the research stage and they are not ready to be introduced into people's homes for continuous use in their daily life. In addition to their low information transfer rates and variable reliability, most current BCI systems are uncomfortable, because the electrodes need to be moistened, the software may require initiation, and the electrode contacts need continuous correction. An easy-to-use P300-based BCI with remote monitoring using a high-speed internet connection has already been proposed to reduce dependence on technical experts.

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