International Journal of Scientific Research Engineering & Technology (IJSRET) ISSN: 2278–0882
EATHD-2015 Conference Proceeding, 14-15 March, 2015

Brain Computer Interface: Next Generation Thought for Human development

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Abstract

Brain computer interface also known as synthetic telepathy interface is an artificial system to establish a direct communication pathway between the brain and an external device that is computer. BCI decodes human intent from brain activity alone to create an alternative communication channel. In these systems, users explicitly manipulate their brain activity instead of using motor movements to produce signals that can be used to control computers or communication devices. The sensor detects the firing rate of a neuron, and firing pattern can be mapped to the person's thoughts that in turn control specific robotic motions. Some of the technical applications of this technology are frivolous, such as the ability to control a video game by thought, ability to change TV channel with your mind etc, while the clinical applications are tremendous. Future progress hinges on attention to a number of crucial factors including recognition as BCI development is an interdisciplinary problem, involving neurobiology, psychology, engineering, mathematics, computer science, and clinical rehabilitation.

Keywords— *Computer Interface, synthetic telepathy, electroencephalography (EEG).*

I. INTRODUCTION

Envision technologies that increase training or rehabilitation effectiveness by integratingreal-time brain activity assessment into individualized, adaptive training and rehabilitation regimens; technologies that help you focus or even overcome a bad day by adjusting your environment to help you achieve desired brain states; technologies that help your doctor identifybrain-based diseases or disorders before they interfere with life by assessing neural activity before behavioural symptoms appear; or even technologies that help you communicate better by assessing the neural activity of your audience and providing suggestions for increased clarity and interest. These are examples of potential brain-computer interface (BCI) technologies, a class of neurotechnologies originally developed for medical assistive applications. While there are a number of potential definitions for this term, in this review we will expand the term BCI to include all technologies that use on-line brain-signal processing to influence human interactions with computers, their environment, and even other humans.

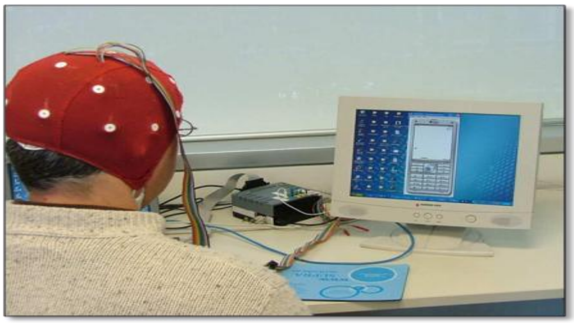

Fig. 1: Brain Computer Interface

II. BCI: AN ARTIFICIAL INTELLIGENCE

A BCI is an artificial intelligence system that can recognize a certain set of patterns in brain signals following five consecutive stages: signal acquisition, pre processing or signal enhancement, feature extraction, classification, and the control interface [1]. BCI creates a new non-muscular system that bypasses the body's normal efferent pathways for relaying a person's intentions to external stimuli. Electrophysiological signals may be recorded over the scalp, underneath the scalp, or within the brain; other types of physiological signals may be recorded by magnetic sensors or other means.BCI technology holds promise to be particularly helpful to people who are "locked-in," cognitively intact but without useful muscle function. Restoration of basic communication capabilities for these people would significantly improve their quality of life. BCI research has undergone an explosive growth in recent years. At present, there are over 400 groups worldwide engaging in a wide spectrum of research and development programs, using a variety of brain signals, signal features, and analysis and translational algorithms [2].

III. COMPONENT OF BCI SYSTEM

The purpose of a BCI is to detect and quantify features of brain signals that indicate the user's intentions and to translate these features in real time into device commands that accomplish the user's intent. To achieve this, a BCI system consists of 4 sequential components (1) signal acquisition, (2) feature extraction, (3) feature translation, and (4) device output. These 4 components are controlled by an operating protocol that defines the onset and timing of operation, the details of signal processing, the nature of the device commands, and the oversight of performance. An effective operating protocol allows a BCI system to be flexible and to serve the specific needs of each user [3].

A. Signal Acquisition

Signal acquisition is the measurement of brain signals using a particular sensor modality (eg scalp or intracranial electrodes for electrophysiological activity, fMRI for metabolic activity). The signals are amplified to levels suitable for electronic processing (and they may also be subjected to filtering to remove electrical noise or other undesirable signal characteristics, such as 60-Hz power line interference). The signals are then digitized and transmitted to a computer.

B. Feature Extraction

Feature extraction is the process of analyzing the digital signals to distinguish pertinent signal characteristics (i.e., signal features related to the person's intent) from extraneous content and representing them in a compact form suitable for translation into output commands. These features should have strong correlations with the user's intent. Because much of the relevant (ie, most strongly correlated) brain activity is either transient or oscillatory, the most commonly extracted signal features in current BCI systems are time-triggered EEG or ECoG response amplitudes and latencies, power within specific EEG or ECoG frequency bands, or firing rates of individual cortical neurons.

C. Feature Translation

The resulting signal features are then passed to the feature translation algorithm, which converts the features into the appropriate commands for the output device (ie, commands that accomplish the user's intent). For example, a power decrease in a given frequency band could be translated into an upward displacement of a computer cursor, or a P300 potential could be translated into selection of the letter that evoked it. The translation algorithm should be dynamic to accommodate and adapt to spontaneous or learned changes in the signal features and to ensure that the user's possible range of feature values covers the full range of device control.

D. Device Output

The commands from the feature translation algorithm operate the external device, providing functions such as letter selection, cursor control, robotic arm operation, and so forth. The device operation provides feedback to the user, thus closing the control loop.

IV. BCI PLATFORMS

Currently, 3 general categories of BCI platforms have been put forward as candidates for clinical applications. These categories are primarily determined by the source from which the controlling brain signal is derived. The first category utilizes EEG, which measures brain signals acquired from the scalp. The second category, referred to as "single-unit systems," utilizes intraparenchymal microelectrodes that detect action potential firings of individual neurons. The third is an intermediate modality in which electrodes acquire signals from the cortical surface directly (either above or below the dura).

A. Electroencephalography-Based Systems

The most commonly studied signals are the electrical signals produced mainly by neuronal postsynaptic membrane polarity changes that occur because of activation of voltage-gated or ion-gated channels. The scalp EEG, first described by Hans Berger in 1929[4] is largely a measure of these signals. Most of the early BCI work used scalp-recorded EEG signals, which have the advantages of being easy, safe, and inexpensive to acquire. The main disadvantage of scalp recordings is that the electrical signals are significantly attenuated in the process of passing through the dura, skull, and scalp [5]. Thus, important information may be lost. The problem is not simply theoretical: epileptologists have long known that some seizures that are clearly identifiable during intracranial recordings are not seen on scalp EEG. Given this possible limitation, recent BCI work has also explored ways of recording intracranial.

B. Single Neuron – Based Systems

From a purely engineering point of view, the optimal method of extracting electrical information from the brain would be to place a series of small recording electrodes directly into the cortical layers (1.5–3 mm) to record signals from individual neurons. This procedure, in essence, is what single-unit action potential BCI systems do, and they have been very successful for limited time periods in both monkeys [6,7,8,9] and humans [10,11]. To extract single-unit activity, small microelectrodes having ~ 20-µm-diameter tips are inserted in the brain parenchyma where relatively large (for example, 300-µV) extracellular action potentials are recorded from individual neurons from 10 to 100 µm away. These signals are usually band pass–filtered from 300 to 10,000 Hz and then passed through a spike discriminator to measure spike time occurrences. The firing rates of individual neurons are computed in 10- to 20-msec bins and "decoded" to provide a high fidelity prediction to control computer cursor or robot end point kinematics[12,13,14]. Given its high spatial resolution (100 µm) as well as its high temporal resolution (50–100 Hz), this modality arguably provides the highest level of control in BCI applications. Unfortunately, there are 2 major problems with single-unit BCIs. First, the electrodes must penetrate into the parenchyma where they not only cause local neural and vascular damage, but also increase the chances for CNS infections.[15] Second, single-unit action potential microelectrodes are very sensitive to encapsulation. The insertion of penetrating devices into brain parenchyma damages neurons and vasculature, which can initiate a cascade of reactive cell responses typically characterized by the activation and migration of microglia and astrocytes toward the implant site [15].

C. Electrocorticography-Based Systems

Small intracortical microarrays like the one implanted in the previously mentioned case of tetraplegia [16] may be embedded in the cortex. These intracortical microarray systems can record the action potentials of individual neurons and the local field potentials (essentially a micro-EEG) produced by a relatively limited population of nearby neurons and synapses. The disadvantages of such implants are the degree of invasiveness, with the need for craniotomy and or craniotomy and neurosurgical implantation, the restricted area of recording, and the still unanswered question of the long-term functional stability of the recording electrodes. In addition to scalp EEG and intracortical BCIs, ECoG-based BCIs use another approach to record brain signals.These BCIs use signals acquired by grid or strip electrodes on the cortical surface[17] or stereotactic depth macroelectrodes that record intraparenchymally[18]or from within the ventricles[19]. These electrode arrays have the advantage of recording intracranial and can record from larger areas of the brain than intracortical microarrays. However, these electrodes also need neurosurgical implantation, and the question of long-term electrode signal recording stability is as yet unanswered. Each of these methods has its own strengths and weaknesses.

V. TYPES OF BCI

The BCIs can be categorized into (i) exogenous or endogenous and (ii) synchronous (cue-paced) or asynchronous (self-paced).

According to the nature of the signals used as input, BCI systems can be classified as either exogenous or endogenous. Exogenous BCI uses the neuron activity elicited in the brain by an external stisuch as VEPs or auditory evoked potentials [20]. Exogenous systems do not require extensive training since their control signals, SSVEPs and P300, can be easily and quickly set-up. Besides, the signal controls can be realized with only one EEG channel and can achieve a high information transfer rate of up to 60 bits/min. On the other hand, endogenous BCI is based on self-regulation of brain rhythms and potentials without external stimuli [20]. Through neurofeedback training, the users learn to generate specific brain patterns which may be decoded by the BCI such as modulations in the sensorimotor rhythms [21] or the SCPs [22]. The advantage of an endogenous BCI is that the user can operate the BCI at free will and move a cursor to any point in a two-dimensional space, while an exogenous BCI may constrain the user to the choices presented. Also, endogenous BCI are especially useful for users with advanced stages of ALS or whose sensory organs are affected.

According to the input data processing modality, BCI systems can be classified as synchronous or asynchronous. Synchronous BCIs analyze brain signals during predefined time windows. Any brain signal outside the predefined window is ignored. Therefore, the user is only allowed to send commands during specific periods determined by the BCI system. For example, the standard Graz BCI [23] represents a synchronous BCI system. The advantage of a synchronous BCI system is that the onset of mental activity is known in advance and associated with a specific cue [24]. Moreover, the patients may also perform blinks and other eye movements, which would generate artifacts, if the BCI did not analyze the brain signals to avoid their misleading effects.

This simplifies the design and evaluation of synchronous BCI. Asynchronous BCIs continuously analyze brain signals no matter when the user acts. They offer a more natural mode of human-machine interaction than synchronous BCI. However, asynchronous BCIs are more computation demanding and complex.

VI. BCI APPLICATION

BCIs offer their users new communication and control channels without any intervention of peripheral nerves and muscles. Hence, many researchers focus on building BCI applications, in the hope that this technology could be helpful for those with severe motor disabilities. The main target populations for BCI applications fall into three classes. The first group includes Complete Locked-In State (CLIS) patients who have lost all motor control, because they may be at a terminal stage of ALS or suffer severe cerebral palsy. The second group comprises Locked-In State (LIS) patients who are almost completely paralyzed, but with residual voluntary movement, such as eye movement, eye blinks, or twitches with the lip. The third group of potential BCI users includes abled bodied people and those with substantial neuromuscular control, particularly speech and/or hand control. BCI have little to offer to the third group, because they can send the same information much more quickly and easily via other interfaces, rather than a BCI. Nowadays, there are a vast number of very different BCI applications, such as word processors, adapted web browsers, brain control of a wheelchair or neuroprostheses, and games, among others.

However, most applications have solely been designed for training or demonstration purposes. Despite the most recent significant advances in BCI technology, there are still many challenges to employing BCI control for real-world tasks [25]: (i) the information transfer rate provided by BCIs is too low for natural interactive conversation, even for experienced subjects and well-tuned BCI systems; (ii) the high error rate further complicates the interaction; (iii) BCI systems cannot be used autonomously by disabled people, because BCI systems require assistants to apply electrodes or signal-receiving devices before the disabled person can communicate; (iv) a BCI user may be able to turn the BCI system off by means of brain activity as input, but usually cannot turn it back on again, which is termed the “Midas touch” problem; and (v) handling BCI applications demands a high . Each of the following applications have been discussed below

A. *Communication*

BCI applications for communication deal with severe communication disabilities resulting from neurological diseases. This kind of application probably represents the most pressing research in the field of BCI, because communication activity is essential for humans. Applications for communication purposes outline an operation that typically displays a virtual keyboard on screen, where the user selects a letter from the alphabet by means of a BCI. The distinguishing element in each approach is usually the BCI and the type of control signal.

B. *Motor Restoration*

Spinal cord injury (SCI) or other neurological diseases with associated loss of sensory and motor functions dramatically decrease the patient’s quality of life and create life-long dependency on home care services. Motor restoration may alleviate their psychological and social suffering. Restoring movement, such as grasping, is feasible in quadriplegic patients through neuroprostheses guided by functional electrical stimulation (FES). BCI can be used to generate a control signal for the operation of FES, because EEG signals are unaffected by electrical activation of upper extremity muscles [27].

C. *Environmental Control*

One of the main goals of BCI-based applications is to achieve maximum independence for the patient, despite any motor disability. People who suffer severe motor disabilities are often homebound and for this reason, environmental control applications focus on the control of domestic devices such as TV, lights or ambient temperatures. Apart from improving the quality of life of severely disabled people, assistive devices mean that the tasks of the caregiver are less intensive, costs are reduced, and the life of relatives is less onerous.

D. *Entertainment*

Entertainment-orientated BCI applications have typically had a lower priority in this field. Until now, research into BCI technology has usually focused on assistive applications, such as spelling devices, wheelchair control/neuroprostheses rather than applications with entertainment purposes [28].

E. *Other BCI Applications*

BCI systems have also been used in a broad variety of applications beyond the traditional areas of communication, motor restoration, environmental control, locomotion, and entertainment. The ability of BCI feedback to induce cortical plasticity may be the basis for medical applications. Users can acquire selective control over certain brain areas by means of neurofeedback, with the aim of inducing behavioral changes in the brain. Neurofeedback provided by a BCI system may improve cognitive performance [29], speech skills [30], affection , and pain management, and has been used in the treatment of mental disorders, such as epilepsy, attention deficit, schizophrenia, depression, alcohol dependence, or paedophilia. On the other hand, brain signal recordings can be used in an assessment of brain functions to evaluate their status in health.

REFERENCES

[1] Khalid M.B., Rao N.I., Rizwan-i-Haque I., Munir S., Tahir F. Towards a Brain Computer Interface Using Wavelet Transform with Averaged and Time Segmented Adapted Wavelets. Proceedings of the 2nd International Conference on Computer, Control and Communication (IC4’09) Karachi; Sindh, Pakistan. February 2009; pp. 1–4.

[2] Vaughan T.M., Wolpaw JR. The Third International Meeting on Brain-Computer Interface Technology: making a difference. IEEE Trans Neural Syst Rehabil Eng. 2006 Jun;14(2):pp. 126–7.

[3] Wolpaw J.R., Birbaumer N., McFarland D.J., Pfurtscheller G., Vaughan T.M. Brain-computer interfaces for communication and control. Clin Neurophysiol. 2002;113(6):pp. 767–791.

[4] Berger H. Uber das electrenkephalogramm des menchen. Arch Psychiatr Nervenkr. 1929;87: pp.527–570

[5] Akhtari M., Bryant H.C., Mamelak A.N. Conductivities of three-layer human skull. Brain Topogr.2000;13(1):pp.29–42

[6] Carmena J., Lebedev M, Crist R, O’Doherty J, Santucci D, Dimitrov D, et al. Learning to control a brain-machine interface for reaching and grasping by primates. PLoS Biol. 2003;1:pp. 193–208

[7] Serruya MD, Hatsopoulos NG, Paninski L, Fellows MR, Donoghue JP. Instant neural control of a movement signal. Nature. 2002;416: pp. 141–142.

[8] Taylor DM, Tillery SI, Schwartz AB. Direct cortical control of 3D neuroprosthetic devices. Science.2002;296: pp.1829–1832.

[9] Velliste M, Perel S, Spalding MC, Whitford AS, Schwartz AB. Cortical control of a prosthetic arm for self-feeding. Nature. 2008;453: pp.1098–1101.

[10] Hochberg LR, Serruya MD, Friehs GM, Mukand JA, Saleh M, Caplan AH, et al. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature. 2006;442: pp.164–171.

[11] Kennedy PR, Bakay RA. Restoration of neural output from a paralyzed patient by a direct brain connection. Neuroreport. 1998;9:pp.1707–1711.

[12] Georgopoulos AP, Schwartz AB, Kettner RE. Neuronal population coding of movement direction.Science. 1986;233: pp.1416–1419.

[13] Moran DW, Schwartz AB. Motor cortical activity during drawing movements: population representation during spiral tracing. J Neurophysiol. 1999;82: pp.2693–2704.

[14] Wang W, Chan SS, Heldman DA, Moran DW. Motor cortical representation of position and velocity during reaching. J Neurophysiol. 2007;97:pp.4258–4270.

[15] Bjornsson CS, Oh SJ, Al-Kofahi YA, Lim YJ, Smith KL, Turner JN, et al. Effects of insertion conditions on tissue strain and vascular damage during neuroprosthetic device insertion. J Neural Eng. 2006;3: pp.196–207

[16] Hochberg L.R., Serruya M.D., Friehs G.M. Neuronal ensemble control of prosthetic devices by a human with tetraplegia. Nature. 2006;442(7099): pp.164–171.

[17] Krusienski D.J., Shih J.J. Control of a visual keyboard using an electrocorticographic brain-computer interface. Neurorehabil Neural Repair. 2011;25(4): pp.323–331.

[18] Krusienski D.J., Shih J.J. Control of a brain-computer interface using stereotactic depth electrodes in and adjacent to the hippocampus. J Neural Eng. 2011;8(2):025006.

[19] Shih J.J., Krusienski D.J. Signals from intraventricular depth electrodes can control a brain-computer interface. J Neurosci Methods. 2012;203(2): pp.311–314.

[20] Kleber B., Birbaumer N. Direct brain communication: neuroelectric and metabolic approaches at Tübingen. Cogn. Process. 2005;6: pp.65–74.

[21] Krusienski D.J., Schalk G., McFarland D.J., Wolpaw J.R. A mu-rhythm matched filter for continuous control of a brain-computer interface. IEEE Trans. Biomed. Eng. 2007;54: pp.273–280.

[22] Hinterberger T., Schmidt S., Neumann N., Mellinger J., Blankertz B., Curio G., Birbaumer N. Brain-computer communication and slow cortical potentials. IEEE Trans. Biomed. Eng. 2004;51: pp.1011–1018.

[23] Pfurtscheller G., Neuper C., Muller G.R., Obermaier B., Krausz G., Schlogl A., Scherer R., Graimann B., Keinrath C., Skliris D., et al. Graz-BCI: State of the art and clinical applications. IEEE Trans. Neural Sys. Rehabil. Eng. 2003;11: pp.1–4.

[24] Tsui C., Gan J. Asynchronous BCI Control of a Robot Simulator with Supervised Online Training. In: Yin H., Tino P., Corchado E., Byrne W., Yao X., editors. Intelligent Data Engineering and Automated Learning—IDEAL 2007. Vol. 4881. Springer; Berlin, Germany: 2007. pp. 125–134.

[25] Moore M.M. Real-world applications for brain-computer interface technology. IEEE Trans. Neural Syst. Rehabil. Eng. 2003;11: pp.162–165.

[26] Sellers E.W., Vaughan T.M., Wolpaw J.R. A brain-computer interface for long-term independent home use. Amyotroph. Lateral Scler. 2010;11: pp.449–455.

[27] Lauer R.T., Peckham P.H., Kilgore K.L. EEG-based control of a hand grasp neuroprosthesis.NeuroReport. 1999;10: pp.1767–1771.

[28] Fun of gaming: Measuring the human experience of media enjoyment. Available online:http://fuga.aalto.fi/

[29] Hanslmayr S., Sauseng P., Doppelmayr M., Schabus M., Klimesch W. Increasing individual upper alpha power by neurofeedback improves cognitive performance in human subjects. Appl. Psychophysiol. Biofeedback. 2005;30: pp.1–10.

[30] Rota G., Sitaram R., Veit R., Erb M., Weiskopf N., Dogil G., Birbaumer N. Self-regulation of regional cortical activity using real-time fMRI: The right inferior frontal gyrus and linguistic processing. Hum. Brain Mapp. 2009;30: pp.1605–1614.