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The Power of Brain: Brain Computer Interfacing.

Shivrajsinh Rayjada

Electronics and Communication Department, B.H.gardi college of engineering and technology, Rajkot

Abstract: - A promising means to give back basic communication abilities and a small degree of autonomy to locked-in persons are BCIs. BCI is used to measure the magnetic and electric activity of the brain. The BCI will be the new way of to communicate from person to person and from person to a machine. Brain–computer interfaces (BCI's) give their users communication and control channels that do not depend on the brain's normal output channels of peripheral nerves and muscles. Different then the communication, BCI can also be used for the purpose of the multimedia. For more you can imagine that a game is being is played by the multiplayer using BCI. Now a days there is explosion of the research in advance in mobile technologies, bio sensors, data acquisition, data transfer, space research, holographic and advance humanoid robot, but now the future will be of the controlling and interfacing of brain with machine rather than any controlling device's. For these BCI will be the upcoming technologies for the future decades.

Keyword: - Power of brain, BCI, Computer Interfacing, Machine Interfacing, Brain Computer Interfacing, Brain Machine Interfacing.

I. INTRODUCTION

The way to communicate with other persons, be it through speech, gesturing, or writing, reacting is one of the main factors making the life of any human being enjoyable. Communication is at the basis of human development, makes it possible to express ideas, desires, and feelings, and on a more ordinary level simply allows to cope with daily life. Individuals suffering from the so-called locked-in syndrome do not have the possibilities of communication mentioned above. In the locked-in syndrome the condition of the patient is like they are aware and conscious but does not able react or move. In fact, the locked-in syndrome is caused by a nearly total loss of control over the voluntary muscles. A disease that is known to lead to the locked-in syndrome is amyotrophic lateral sclerosis (ALS), also known as Lou Gehrig's disease. ALS is a progressive, neurodegenerative disease and is characterized by the death of motor neurons which in turn leads to the loss of control over voluntary muscles. Besides ALS also multiple sclerosis, stroke or other cerebrovascular incidents leading to the infarction or degeneration of parts of the brain can cause the locked-in syndrome. Hence, the quality of life of persons affected by the locked-in syndrome is strongly diminished by the lack of possibilities to communicate with other persons and by the complete loss of autonomy.

II. PAST AND PRESENT SCENARIO

Brain–computer interface (BCIs) was started with Hans Berger's inventing of electrical activity of the human brain and the development of electroencephalography (EEG). In 1924 Berger recorded an EEG signals from a human brain for the first time. By analysing EEG signals Berger was able to identify oscillatory activity in the brain, such as the alpha wave (8–12 Hz), also known as Berger's wave.

The first recording device used by Berger was very elementary, which was in the early stages of development, and was required to insert silver wires under the scalp of the patients. In later stages, those were replaced by silver foils that were attached to the patients head by rubber bandages later on Berger connected these sensors to a Lippmann capillary electrometer, with disappointing results. More sophisticated measuring devices such as the Siemens double-coil recording galvanometer, which displayed electric voltages as small as one ten thousandth of a volt, led to success. Berger analysed the interrelation of alternations in his EEG wave diagrams with brain diseases. EEGs permitted completely new possibilities for the research of human brain activities.

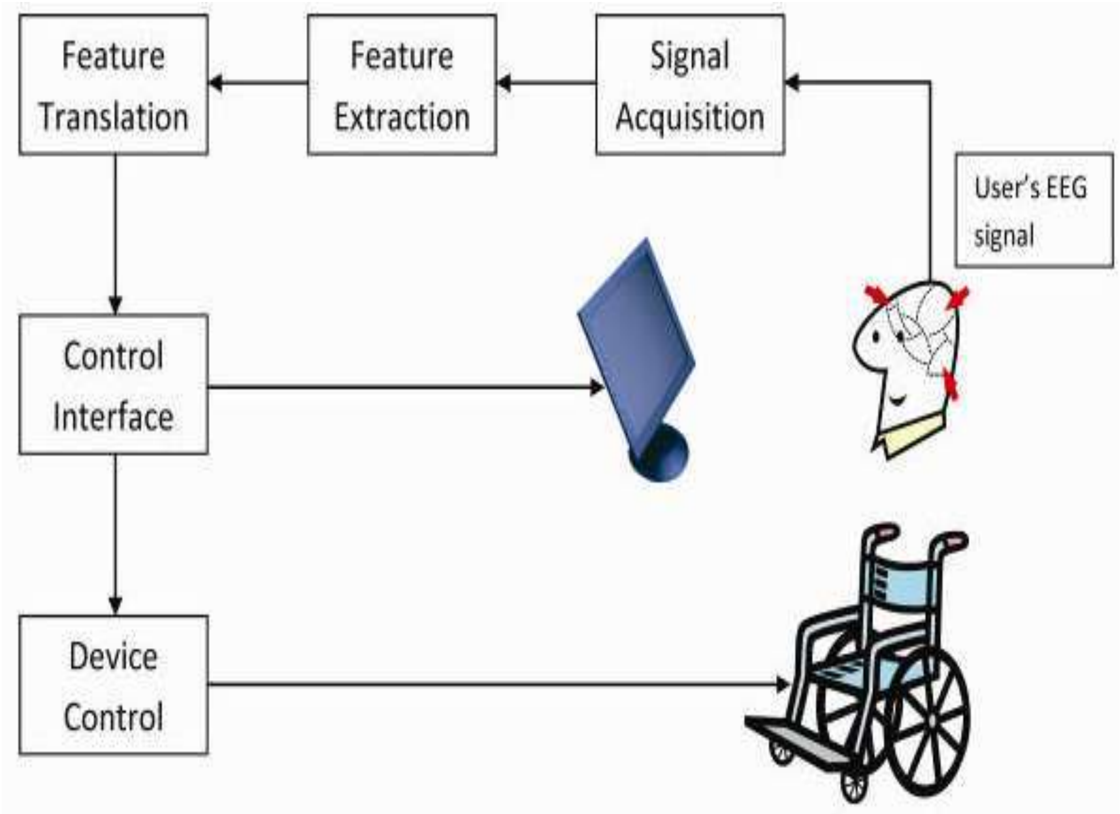

Figure 1. Overviews of Brain Computer Interface (BCI)

A. Functional Components of Brain Computer Interface

A Brain Computer Interfacing (BCI) is also called Mind Machine Interfacing (MMI) or sometimes it also called as Brain Machine Interface (BMI).

The BCI is the direct communication between the brain and the machine. The person can control a machine his/her thoughts. BCI is useful for the person who is deaf or dumb, it is also helpful for the who are paralyzed and cannot move their body parts and faces and doesn't express their feeling by the mean of gesture's and posture's. For such kind of person the Brain Computer Interfacing (BCI) is boon from the technologies in their life.

B. BCI Operation

Any BCI, regardless of its recording methods or applications, consists of four essential elements, as described by Wolpaw: 1) signal acquisition, 2) feature extraction; 3) feature translation; and 4) device output. Figure illustrates the essential elements and operation of a BCI system, as well as its clinical applications. These four elements are managed through the system's operating protocol. Since BCIs based on electrophysiological signals are in the most advanced state of development and have resulted in some clinical applications, the remainder of this article focuses on BCIs of this type.

C. Signal Acquisition

Signal acquisition is the measurement of the neurophysiologic state of the brain. In BCI operation, the recording interface (i.e., electrodes, for electrophysiological BCI systems) tracks neural information reflecting a person's intent embedded in the on-going brain activity. As discussed in the last section, the most common electrophysiological signals employed for BCI systems include: EEG recorded by electrodes on the scalp; ECoG recorded by electrodes placed beneath the skull and over the cortical surface; and local field potentials (LFPs) and neuronal action potentials (spikes) recorded by microelectrodes within brain tissue. The brain electrical signals used for BCI operation are acquired by the electrodes, amplified, and digitized.

D. Feature Extraction

The signal-processing stage of BCI operation occurs in two steps. The first step, feature extraction, extracts signal features that encode the intent of user. In order to have effective BCI operation, the electrophysiological features extracted should have strong correlations with the user's intent. The signal features extracted can be in the time-domain or the frequency-domain. The most common signal features used in current BCI systems include: amplitudes or latencies of event-evoked potentials (e.g., P300), frequency power spectra (e.g., sensorimotor rhythms), or firing rates of individual cortical neurons. An algorithm filters the digitized data and extracts the features that will be used to control the BCI. In this step, confounding artefacts (such as 60-Hz noise or EMG activity) are removed to ensure accurate measurement of the brain signal features.

E. Feature Translation

The second step of signal processing is accomplished by the translation algorithm, which converts the extracted signal features into device commands. Brain electrophysiological features or parameters are translated into commands that will produce output such as letter selection, cursor movement, control of a robot arm, or operation of another assistive device.

A translation algorithm must be dynamic to accommodate and adapt to the continuing changes of the signal features and to ensure that the possible range of the specific signal features from the user covers the full range of device control.

F. Device Output

The signal features thus extracted and translated provide the output to operate an external device. The output might be used to operate a spelling program on a computer screen through letter selection, to move a cursor on a computer screen, to drive a wheelchair or other assistive devices, to manipulate a robotic arm, or even to control movement of a paralyzed arm through a neuroprosthesis. At present, the most commonly used output device is the computer screen, and it is used for communication.

G. Operating Protocol

The operating protocol determines the interactive functioning of the BCI system. It defines the onset/offset control, the details of and sequence of steps in the operation of the BCI, and the timing of BCI operation. It defines the feedback parameters and settings, and possibly also any switching between different device outputs. An effective operating protocol allows a BCI system to be flexible, serving the specific needs of an individual user.

At present, since most BCI studies occur in laboratories under controlled conditions, investigators typically control most of the parameters in the protocol, providing simple and limited functionality to the BCI user. More flexible and complete operating protocols will be important for BCI use in real life, outside of the laboratory.

Types of BCI: The early work of BCI was done by invasive methods with electrodes inserted into the brain tissue to read the signals of a single neuron. Although the Spatio-temporal resolution was high and the results were highly accurate, there were complications in the long term. These were mostly attributable to the scar tissue formation, which leads to a gradual weakening of the signal and even complete signal loss within months because of the brain tissue reaction towards the foreign objects. A proof of concept experiment was done by Nicolelis and Chapin on monkeys to control a robotic arm in real time using the invasive method.

Now a day less invasive methods have been used by applying an array of electrodes in the subdural space over the cortex to record the Electrocorticogram (ECoG) signals. It has been found that ordinary Electroencephalogram pickup signals are averaged over several square inches whereas ECoG electrodes can measure the electrical activity of brain cells over a much smaller area, thereby providing much higher spatial resolution and a higher signal to noise ratio because of the thinner barrier tissue between the electrodes and the brain cells. The superior ability to record the gamma band signals of the brain tissue is another important advantage of this type of BCI system. Gamma rhythms (30-200 Hz) are produced by cells with higher oscillations, which are not easy to record by ordinary EEGs. The human skull is a thick spatial filter, which blurs the EEG signals, especially the higher frequency bands (i.e. gamma band).

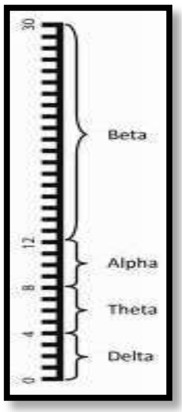

Figure 2. Brain wave spectrum

Table 1. Brain wave spectrum analysis

Type	Frequency	Location	Use
Delta	<4 Hz	Everywhere	Occur during sleep and coma
Theta	4-7 Hz	Temporal and parietal	Correlated with emotional stress (frustration and disappointment)
Alpha	8-12 Hz	Occipital and parietal	Reduce amplitude with sensory stimulation or mental imagery
Beta	12-36 Hz	Parietal and frontal	Can increase mental amplitude during intense mental activity
Mu	9-11 Hz	Frontal (motor cortex)	Diminishes with movement or intense of movement
Lambda	Sharp, jagged	Occipital	Correlated with visual attention
Vertex			Higher incidence in patience with epilepsy or encephalopathy

Non-invasive techniques were demonstrated mostly by electroencephalographs (EEG). Others used functional Magneto-Resonance Imaging (fMRI), Positron Electron Tomography (PET), Magneto encephalography (MEG) and Single Photon Emission Computed Tomography (SPECT). EEGs have the advantage of higher temporal resolution, reaching a few milliseconds and are relatively low cost. Recent EEG systems have better spatiotemporal resolution of up to 256 electrodes over the total area of the scalp. Nevertheless, it cannot record from the deep parts of the brain. This is the main reason why the multimillion dollar fMRI systems are still the preferred method for the functional study of the brain. However, EEG systems are still the best candidate for BCI systems as they are easy to use, portable and cheap.

Table 2. Different techniques for BCI

Technique	Physical property	Measurement mechanism	Advantages	Disadvantages
(EEG)	Electrical Potential	Electrode are placed carefully on scalp in order to measure the weak (5-100µv) electrical potential generated by neural activity in the brain.	Portable, wearable High temporal resolution (tens or hundreds of millisecond)	Low spatial resolution (at best 1-2 cm usually more) due to noise added when signal move through fluid, bones, skin. Requires carefull placement of electrodes directly on scalp.
(MEG)	Magnetic Potential	Measures magnetic fields generated by the electrical activity of brain.	MEG enables much deeper imaging and much more sensitive than EEG since skull is almost completely to magnetic waves.	Bulky and expensive equipment due to necessity for super conductivity.
(PET)	Blood flow	Detects chemical activity of injected radioactive traces by measuring gamma ray emission.		Bulky and expensive equipment unsuitable for sustained use due to need to inject radioactive substances.
(SPECT)	Blood flow	Works like PET except that user photo multiplier tubes to measure generated by gamma rays.	Slightly less expensive than PET.	Low temporal and spatial resolution than PET. Bulky and expensive equipment unsuitable for sustained use due to need to inject radioactive substances.
(FMRI)	Blood flow	Measure magnetic properties of blood to determine the decrease in deoxyhemoglobin to active brain region (increase blood flow to these region is not accompanied by proportional increase in oxygen consumption).	Highly spatial resolution (1mm-1cm)	Low temporal resolution (5-8 seconds) because in flow of blood is not an immediate phenomenon. Bulky and expensive equipment due to need of superconducting magnets.
(FNIR)	Blood flow, changes in cortical tissue.	Measure the absorption and scattering of near infrared light direct into the brain to determine change in tissue oxygenation (slow response) as well as change in neuronal membranes during neuron firing (fast event related response).	High speed resolution (< 1cm) Similarities to FMRI allows transfer of knowledge Inexpensive equipment Portable, wearable. Does not require large amount of expertise to set up. Non-ionizing light safe for extended use.	Low temporal resolution (5-8 seconds) when using slow response measurement.

III. PRONES AND CONES OF BCI

The main challenge lies in the brain itself. The brain usually has numerous neuron centers that cooperate to produce single smooth limb movements. The question is whether the brain is capable of training specific neurons to act as internetworking neuron center's that control the limbs through the spinal cord way to produce a smooth limb movement. BCI capacity and efficiency depend on the answer to this question. Previous studies indicate that the ability to train specific neuron cells to control an artificial prosthesis smoothly is far more problematic with high variability from trial to trial compared to the usual way of controlling the limbs through the spinal cord. This deficit in the brain's ability is not dependent upon the type of BCI or whether it was done by measuring the activity of cortical neurons or the EEG power spectrum. This suggests that this control deficit cannot be enhanced by developing better recording techniques.

Better translation algorithms will likely emerge in the future, making the control more realistic and more efficient, however, the severity and the nature of this deficit in current BCI research indicates that a more realistic translation algorithm should be developed that decreases the challenge to the extent that the challenge is the same as controlling through normal muscle based control.

IV. APPLICATION OF BCI.

A. Spelling Devices:

Spelling devices allow severely disabled users to communicate with their environment by sequentially selecting symbols from the alphabet. One of the first spelling devices mentioned in the BCI literature is the P300 speller. Another system, tested with users suffering from ALS and based on SCPs was described by Birbaumer.

B. Environment Control:

Environment control systems allow to control electrical appliances with a BCI. A proof-of-concept environment control system based on SSVEPs. The control of a virtual apartment with a BCI using the P300.

C. Wheelchair Control:

A BCI can potentially be used to steer a wheelchair. Because steering a wheelchair is a complex task and because wheelchair control has to be extremely reliable, the possible movements of the wheelchair are strongly constrained in current prototype systems. For example the wheelchair is constrained to move along paths predefined in software, joining registered locations, and a P300-based interface is used to select the desired location.

D. Neuromotor Prostheses:

The idea underlying research on neuromotor prostheses is to use a BCI for controlling movement of limbs and to restore motor function in tetraplegics or amputees. Different types of neuromotor prostheses can be envisioned depending on the information transfer rate a BCI provides. If neuronal ensemble activity is used as control signal, high information transfer rates are achieved and 3D robotic arms can be controlled.

If an EEG based BCI is used, only simple control tasks can be accomplished. For example in the system described by [27 sensorimotor rhythms were used to control functional electric stimulation of hand muscles and so to restore grasp function in a tetraplegics patient.

E. Gaming and Virtual Reality:

Besides the applications targeted towards disabled subjects, prototypes of gaming and virtual reality applications have been described in the literature. Examples for such applications are the control of a spaceship with oscillatory brain activity and the control of an animated character in an immersive 3D gaming environment with SSVEPs.

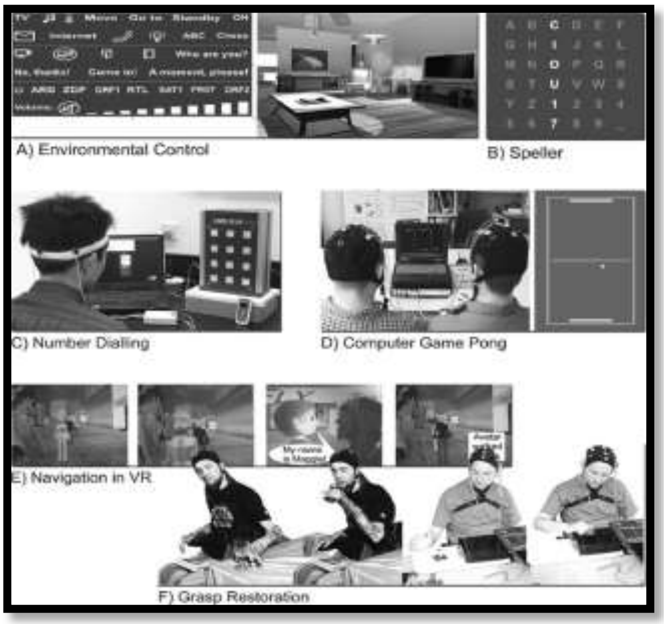

Figure 3. Examples of BCI applications

(A) Environmental control with a P300 BCI (see chapter “The First Commercial Brain–Computer Interface Environment”),

(B) P300 Speller (see chapter “BCIs in the Laboratory and at Home: The Wadsworth Research Program”),

(C) Phone number dialling with an SSVEP BCI (see chapter “Practical Designs of Brain–Computer Interfaces Based on the Modulation of EEG Rhythms”),

(D) Computer game Pong for two players,

(E) Navigation in a virtual reality environment (see chapter “The Graz Brain–Computer Interface”),

(F) Restoration of grasp function of paraplegic patients by BCI controlled functional electrical stimulation.

V. CONCLUSION

The use of EEG signals as a vector of communication between man and machines represents one of the current challenges in signal theory research. The principal element of such a communication system is known as “Brain Computer Interface”. BCI is the interpretation of the EEG signals related to the characteristic parameters of brain electrical activity. This is the new emerging area which is mainly for the patients in the treatment bed (those have lost their speech due to accident or with any reason). Over the past few years, numerous proof-of-concept experiments have shown that people unable to move can use simple EEG-based BCI systems for point-and-click, robot control, and even spelling at rates as fast as 20 words per minute.

However it has its own drawbacks. EEG measures tiny voltage potentials where signal is weak and prone to interference. Signals have to be recorded from brain in a clinical condition where there are no external (noise free environment), users have to be trained to perform various tasks with full concentration and Handling high dimensional data.

Future work in this regard would be exploring different approaches which can increase the reliability of scalp EEG recordings, exploring some more dimension reduction algorithms which helps in reducing the size of the EEG features. We can also say as detection techniques and experimental designs improve, the BCI will improve as well and would provide wealth alternatives for individuals to interact with their environment.

In the far-term, we envision a more holistic approach to BCIs that merges critical brain, behavioural, task, and environmental information obtained with advanced pervasive, multi-aspect sensing technologies, sophisticated analytical approaches, and enabled by advances in computational infrastructure such as extensions of cloud technologies. Such an approach may also benefit from exploring synergies between the human and the computer as well as the large-scale collection of data consisting of both brain function (e.g. EEG, fMRI) and brain structure (e.g. diffusion weighted imaging) at multiple scales, ranging from individual neurons up to maps of the entire brain. This data could provide a great deal of insight into how differences and changes in physical brain structure, both within and between individuals, cause changes in the functional brain data that can be detected in real time, thus providing much greater capabilities to individualized BCI technologies.

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