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SURVEY ARTICLE

TECHNOLOGY BOON: EEG BASED BRAIN COMPUTER INTERFACE - A SURVEY

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Abstract— The BCI research has now witnessed incredible expansion using invasive and non- invasive methods but especially the use of Electroencephalogram (EEG) signals (method of non-invasive BCI) has attained a lot of significance. The applications of EEG based BCI ranges from medicine to entertainment. In this paper, a general Electro-Encephalogram (EEG) based BCI system is discussed. Thus development of an EEG based brain-computer interface (BCI) devices could be the most important technological breakthrough in decades [3], which, primarily aim to improve the eminence of life of the disabled peoples to operate Computer devices and applications through their mental activities.

Key Terms: - BCI; EEG; Neuroimaging; Feature extraction; classifiers

I. INTRODUCTION

The brain use bodies to interact with the external world and, under some circumstances, brains can be deprived of their sensing abilities (for example, blindness or deafness) or motor abilities (for example, paralysis) [2]. The general concept is therefore to either create artificial sensory systems or to allow the brain to directly command and control external devices, such as computer system, mobile phones etc. Thus development of a brain-computer interface (BCI) devices could be the most important technological breakthrough in decades [3], which, primarily aim to improve the eminence of life of the disabled peoples to operate Computer devices and applications through their mental activities.

Brain-Computer Interface (BCI) is nothing but a communication system, which enables the user to control special computer applications by using only his or her thoughts. The general purpose BCI system takes neural signals as inputs, which is the fundamental element of any BCI system and then process this signal, extracting features from it, classifying them and consequently converting these recognized signals into device control commands and invocation of the desired actions. A general BCI system is depicted in figure 1.

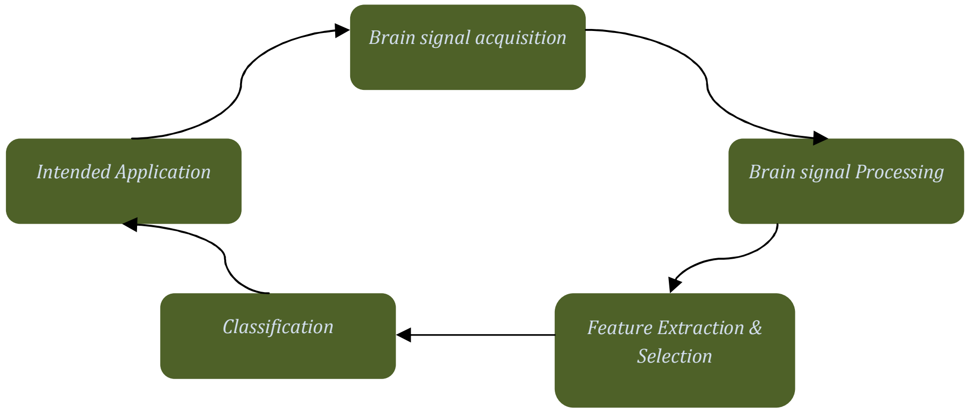

Figure 1: General BCI System

BCI can be classified into Invasive and Non-invasive BCI. Invasive BCIs are implanted directly into the grey matter of the brain using neurosurgery. Invasive devices produce the highest quality signals of BCI devices (Wikipedia) while non-invasive does not include any surgery rather he signals are acquired from the surface of brain itself [10].

This paper is organized into following sections/chapters. Chapter 2 details about various important brain signal acquisition techniques. Chapter 3 describes for signal preprocessing while Feature Extraction details are covered in Chapter 4. Various Classifiers and their usage in BCI are given under Chapter 5 and Chapter 6 describes applications.

II. BRAIN SIGNAL ACQUISITION TECHNIQUES

The foremost step for a BCI system is to acquire brain signals. There are various Neuroimaging techniques available out of which functional methods are used for BCI research instead of anatomical methods. They consist of direct methods as (Electroencephalography (EEG), Magnetoencephalography (MEG), Fetal magnetoencephalography (fMEG)) and indirect methods (Positron-emission-tomography (PET), Single photon emission computed tomography (SPECT), Functional magnetic resonance imaging (fMRI), Near infrared spectroscopy (NIRS)) of measuring neural activities[1, 19].

Brief descriptions of some of majorly used Neuroimaging methods are as follows:

EEG: The Electroencephalogram (acronym EEG) is a diagnostic tool that records the electrical activity of the brain using numerous electrodes placed on the scalp. The electrical activity is produced by the brain cells (neurones) and neural circuits.

MEG: Magnetoencephalography (MEG) is a non-invasive neurophysiological technique that measures the magnetic fields generated by neuronal activity of the brain. The spatial distributions of the magnetic fields are analyzed to localize the sources of the activity within the brain, and the locations of the sources are superimposed on anatomical images, such as MRI, to provide information about both the structure and function of the brain [4].

All figures of Section II are taken from Google images. The machine is shown in figure 2 below.

Figure 2: MEG Machine

MRI: In this the subject is placed in a strong magnetic field. Radio waves excite hydrogen atoms in the body, thus return of the excited hydrogen atoms to the unexcited state causes a release of radio waves. Detectors in the scanner measure the emitted radio waves [7]. Using the measure of emitted radio waves and the known orientation and magnitude of the magnetic field, a computer calculates the location and magnetic properties of the hydrogen atoms in the body. The machine is shown in figure 3 below.

Figure 3: MRI Machine

fMRI: Same basic theory and technique is used for functional MRI as used in structural MRI. It uses the BOLD (Blood Oxygen Level Detection) response. Several images are taken over a time period and stimuli are presented during the scan[7].

PET: In Positron-emission-tomography the subject is injected with labeled tracer (Flurodeoxyglucose -FDG). During the tracer uptake period (30 min) the subject is presented with a set of stimuli or a task. Immediately following the uptake period, the subject is placed in the scanner and imaged.

Figure 4: PET Machine

SPECT: Single Photon Emission Computed Tomography detects a different type of photon. SPECT provides lower resolution but is much less expensive than PET, usually used for early detection of dementias – evidenced by hypo perfusion in a given area. The machine is shown in figure 5 below.

Figure 5: SPECT Machine

TMS: Tran cranial magnetic stimulation is a method used to stimulate brain tissue by applying strong magnetic fields to particular brain areas. The machine is shown in figure 6 below.

Figure 6: TMS Machine

III. EEG BCI SIGNAL PREPROCESSING

As described in Section 2 above the most convenient method used for BCI is EEG which is non-invasive method for recording Brain Signals. EEG based BCI can be classified as either synchronous or asynchronous. The computer drives synchronous systems by giving the user a cue to perform a certain mental action and then recording the user's EEG patterns in a fixed time-window. Asynchronous systems, on the other hand, are driven by the user and operate by passively and continuously monitoring the user's EEG data and attempting to classify it.

EEG waves are measured using electrodes attached to the scalp which are sensitive to changes in postsynaptic potentials of neurons in the cerebral cortex. The electrodes can be fixed on a cap that is to be worn by the subject. The electrodes placement is done using 10-20 international system. The electrodes, EEG Machine, Electrode placement and the EEG Cap are shown in figure 7

EEG Signals can be classified as shown in table 1 below:

Band	Frequency (Hz)
Delta	1
Theta	4
Alpha	7
Beta	13
Gamma	30+

Table 1: EEG Signals classification [10]

Delta: It tends to be the highest in amplitude and the slowest waves. It is seen normally in adults in slow wave sleep.

Theta: Theta is seen normally in young children. It may be seen in drowsiness or arousal in older children and adults; it can also be seen in meditation.

Alpha: It emerges with closing of the eyes and with relaxation, and attenuates with eye opening or mental exertion.

Beta: It is seen usually on both sides in symmetrical distribution and is most evident frontally. Beta activity is closely linked to motor behavior.

Gamma: Gamma rhythms are thought to represent binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function.

Figure 7: EEG Electrodes, Cap, Machine and electrodes placement map

Now for processing these EEG Signals we have various methods available. Commonly include the Fast Fourier Transform (FFT), the Wavelet Transformation, Blind Signal Separation, and EOG Monitoring [6].

FFT: In order to analyse the data signal for its frequency content, it has to be converted from the time domain into the frequency domain. This can be accomplished by applying a mathematical method known as Fourier Transform. In the context of EEG analysis, the Fourier Transform is applied (once for each channel) to a finite number of discrete data points belonging to successive sometimes overlapping) segments of equal length.

Wavelet Transformation: The basic functions of the Wavelet Transform – the Wavelets – are not any periodic sine and cosine waves that stretch out to infinity, but "small waves" with compact support, being non-zero only in a finite interval.

The resolution feature comes from the set of all basis functions involved in any particular wavelet analysis, which comprises scaled, contracted, and dilated versions of a so-called mother wavelet [18].

The wavelet transformation is achieved by the breaking up of a signal into shifted and scaled versions of the original (or mother) wavelet. A wavelet is a waveform of effectively limited duration with zero mean. Regardless of its mathematical properties, a basic requirement of the wavelet used is that it looks similar to the signal patterns to be localized. Local features can be described better with wavelets that have local extent. It minimizes spurious effects in the reconstruction of the signal via the inverse wavelet transform.

Blind Signal Separation: this method is to isolate those independent signal sources, and applying further processing only to a limited number of isolated signals promises to yield a much better classification performance [5].

IV. BRAIN SIGNAL CLASSIFICATIONS

In order to find out what the user wants, a BCI system has to classify the preprocessed data. This means that the system does not attempt to understand the user's intentions, but it "compares" the data symbolizing a segment to representatives of a limited number of classes, and selects the class matched best.

They are divided into five different categories as linear classifiers, neural networks, nonlinear Bayesian classifiers, nearest neighbor classifiers and combinations of classifiers [1, 2]. Few of them are discussed in the following table 2 [12].

Classifiers	Types	Application Area
Linear Classifiers	Linear Discriminant Analysis (LDA)	A P300-based BMI system developed for remote writing using human brain-actuated robot arm. [16].
	Support Vector Machine (SVM).	A spelling application for paralyzed patients (suffering from focal epilepsy) [8].
Neural Networks	Back Propagation BP network	A new EEG recognition algorithm for integrating discrete wavelet transform (DWT) with BP neural network [5].
	Multilayer Perceptron	
	Learning Vector Quantization (LVQ) Neural Network	
Nonlinear Bayesian classifiers	Bayes quadratic	Virtual Reality BCI Application
	Hidden Markov Model	
Nearest Neighbor classifiers	k Nearest Neighbors	An application to extract features that the user can control and translate into device commands [2]
	Mahalanobis distance	

Table 2: Some commonly used Classifiers in BCI

V. BCI APPLICATIONS

.Brain Computer Interface has tremendous applications using different Classifiers, Feature extraction Method, Brain signal acquisition techniques. Few applications in this field are given in Table 3:

Sl. No	Name and affiliation	Name of work	Brief Description	Reference, if any
1	Politecnico di Milano, Artificial Intelligence and Robotics Lab (AIR Lab)	Driving a wheel chair using BCI	Using a Brain Computer Interface to issue commands to an autonomous wheelchair	http://www.airlab.elet.polimi.it
2	Neurobotics: Brain Machine Interfaces	The dream life of Rats	Controlling Rat's brain using BMI, EEG. Project is funded by DARPA	
3	Brain Machine Interface Technology by Honda and ATR	Enabling control of a robot by human thought alone	BMI is used to control Asimo, Honda's Humanoid Robot	

Sl. No	Name and affiliation	Name of work	Brief Description	Reference, if any
4	Pioneer Emotive Systems	Emotive EPOC (Dec. 2008)	A Neuro headset for gaming. The set detects conscious thoughts, expressions and non-conscious emotions based on electrical signals around the brain. It opens up a plethora of new applications which can be controlled with our thoughts, expressions and emotions.	www.Sciencedaily .com
5	University of Southampton	Brain to brain communication using BCI (Oct. 6, 2009)	A experiment had one person using BCI to transmit thoughts, translated as a series of binary digits, over the internet to another person whose computer receives the digits and transmits them to the second user's brain through flashing an LED lamp. The encoded information is then extracted from the brain activity of the second user and the PC can decipher whether a zero or a one was transmitted. This shows true brain-to-brain activity.	www.Sciencedaily .com
6	Macquarie University, Sydney	DesIRe, Drive (Dec.27, 2008)	A computer system architecture that can carry out "gesture recognition". In this system, the person wears "data gloves" which have illuminated LEDs that are tracked by two pairs of computer webcams working to produce an all-round binocular view. This allows the computer to monitor the person's hand or shoulder movements. This input can then be fed to a program, a game, or simulator, or to control a character, an avatar, in a 3D virtual environment.	
7	Group of international universities and Research Institutes, g.tec	Virtual Smart Home controlled by your thoughts (May26, 2009)	The technology, which was demonstrated at CeBIT in Hannover in March, provides an innovative way of controlling the interconnected electronic devices that will populate the smart homes of the future, granting increased autonomy to people with physical disabilities as well as pleasing TV channel-surfing couch potatoes.	www.Sciencedaily .com

Table 3: Some of Research work done in BCI Field

VI. CONCLUSION AND FUTURE WORK

Brain Computer Interface goes through many phases: signal acquisition, Brain Signal Acquisition, Brain Signal Preprocessing, Feature Extraction and Selection, Classification, and the intended application. The brain signal acquisition involves many methods including invasive and non-invasive methods. Similarly lots more options are there to choose from feature Extraction methods and Classification methods with a major focus on EEG based BCI.

The future work includes Identifying, analyzing words, emotions/feelings through brain signals. By reading brains and analyzing emotions/feelings through brain signals, it would be quite easy to: detect decision making, verify whether a terrorist might be familiar with the scene of a crime, and determine whether someone is really telling the truth. Next, by applying the methods and issues, so identified and analyzed, to the development of software for identifying words/emotions and establish connectivity in human understandable form is another task to be carried out.

REFERENCES

[1] Li Yi , Fan Yingle, Tong Qinye, ―EEG Feature Detection and Classification Algorithm in Brain-Computation Interface‖, 3rd IEEE Conference on Industrial Electronics and Applications (ICIEA), pp. 1403 – 1407, Singapore, June 3-5, 2008.

[2] Li Ming-Ai; Wang Rui; Hao Dong-Mei; Yang Jin-Fu, ―Feature Extraction and Classification of Mental EEG for Motor Imagery‖, Proceedings of the 2009 Fifth International Conference on Natural Computation, pp. 139 – 143, Tianjin, Aug 14-16,2009 .

[3] D Pérez-Marcos, J A Buitrago, F D Giraldo, Velásquez, ―Writing through a robot: a proof of concept for a brain-machine interface‖, Med Eng Phys, vol. 33, no. 10, pp.1314-7, Dec 2011.

[4] Vigario R, Sarela J, Jousmaki V, Hamalainen M, Oja E. Independent component approach to the analysis of EEG and MEG recordings. IEEE Trans Biomed Eng. 47(5): 589-93, 2000

[5] L. Zhang, A. Cichocki, and S. Amari, "Self-adaptive blind source separation based on activation functions adaptation," IEEE Transactions on Neural Networks, vol. 15, no. 2, pp. 233– 244, 2004.

[6] Ernst Niedermeyer and Fernando Lopes da Silva, Electroencephalography: basic principles, clinical applications, and related fields.: Lippincott Williams & Wilkins, 2004.

[7] CE Levy and et al, "Functional MRI evidence of cortical reorganization in upper-limb stroke hemiplegia treated with constraint-induced movement therapy," Am J Phys Med Rehabil, pp. 4-12, 2001.

[8] Support vector machine (http://en.wikipedia.org/wiki/support vector machine).

[9] J. J. Vidal, "Toward direct brain–computer communication," Annu. Rev. Biophys. Bioeng., pp. 157–180, 1973.

[10] G. Pfurtscheller, C. Neuper, D. Flotzinger, and M. Pregenzer, "EEGbased discrimination between imagination of right and left hand movement," Electroenceph. Clin. Neurophysiol., vol. 103, pp. 642–651, 1997.

[11] E. Tamil ,et al. " Electroencephalogram (EEG) Brain Wave Feature Extraction Using Short Time Fourier Transform ", Faculty of Computer Science and Information Technology, University of Malaya,2007.

[12] C Bishop. Neural Networks for Pattern Recognition. Oxford Univ., 1995.

[13] Impact Assessment of Neuroimaging

[14] http://web.mit.edu/kitmitmeg/whatis.html

[15] Poulos, M., M. Rangoussi and N. Alexandris (1999). Neural Network Based Person Identification Using EEG Features. In: Proceedings of the IEEE International Conference on Acoustics, Speech, and Signal Processing.Vol. 2. pp. 1117–1120.

[16] Wolpaw J. R., Birbaumer N., McFarland D. J., Pfurtscheller G., and Vaughan T. M. (2002) "Brain–computer interfaces for communication and control Clinical Neurophysiology, 113, pp 767–791

[17] B. Blankertz, G. Curio, and K. R. Muller, "Classifying single trial EEG: towards brain-computer interfacing," in: T. G. Dietrich, S. Becker, and Z. Ghahramani, eds., Advances in Neural Inf. Proc. Systems (NIPS 01), vol. 14, 2002

[18] Schmidt, R. A. (1982). Motor control and learning: A behavioral emphasis. Human Kinetics Publishers. Champaign, Ill.

[19] Statsny, J. Analysis of states in EEG signals. M. Sc. Thesis.Prague: Czech Technical University, 2001. (In Czech)

