

Chapter 12

A Review on Brain Imaging Techniques for BCI Applications

Saugat Bhattacharyya
Jadavpur University, India

Poulami Ghosh
Jadavpur University, India

Anwasha Khasnobish
Jadavpur University, India

Ankita Mazumder
Jadavpur University, India

D. N. Tibarewala
Jadavpur University, India

ABSTRACT

Evolution has endowed human race with the most adroit brain, and to harness its potential to the fullest the concept of brain computer interface (BCI) has emerged. One of the most crucial components of BCI is the technique of brain imaging. The first approach in the field of brain imaging was to measure the electrical and magnetic activity of the brain, the techniques being known as Electroencephalography and Magnetoencephalography. Striving for furtherance, researchers came up with another alternative known as Magnetic Resonance Imaging. But it being confined to only structural imaging, the functional aspects of brain were mapped using functional magnetic resonance imaging. A similar but comparatively newer neuroimaging modality is Functional Near Infrared Spectroscopy. Transcranial Magnetic Stimulation neuro-physiological technique is based on the principle of electromagnetic induction. Based on nuclear medicine the brain imaging technologies that are widely explored in the world of BCI are Positron Emission Tomography and Single Positron Emission Tomography.

INTRODUCTION

The idea of communicating with computers just by thought has intrigued mankind for a long time and the advent in cognitive science and a large number of technologies for mapping the brain activity has helped it to become a reality. The mapping of neural signals or imaging of activities taking place in different regions of the human brain has been made possible by using different sensors which have the capability of detecting any physical change in those regions. At the beginning, scientists thought that, this system

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will be very helpful for reinstating people with disabilities to their former state and improve the quality of life (Lebedev, M. A., 2006). For that purpose, people are trained to manipulate their thought so as to control the external device (e.g. prosthetic arm, wheelchair and likewise). This technology is particularly useful for providing rehabilitation to people suffering from various neural diseases like amyotrophic lateral sclerosis (Nijboer, F.*et al.*, 2008), paralysis (Birbaumer, N.*et al.*, 2008), cerebral palsy and also to people who have lost one or more of their limb(s) (Neuper, C.*et al.*, 2003). Apart from rehabilitation, brain computer interface (BCI) has found application in various other domains like communication (Wolpaw, J. R.*et al.*, 2002), computer gaming (Krepki, R.*et al.*, 2007), robot control (Galán, F.*et al.*, 2008) and virtual reality.

A brain computer interface (BCI) basically translates the thought to the machine action (computer) by decoding the brain activities. The signals generated by the nerves in the brain are acquired first and then a number of steps are undergone to find out whether these signals form a pattern or not. The main objective of any BCI system is to detect any such pattern from the neural activity of a person's brain and then decode the actual intent of that person from it to drive or communicate with machines. This system then converts the acquired signals into machine understandable signals so that those can be used for controlling any external device. There are mainly three types of BCI systems available, namely invasive, partially-invasive and non-invasive BCI (Vourvopoulos, A.*et al.*, 2012). In case of non-invasive BCIs, the signals are acquired superficially using a number of technologies. The invasive BCIs are used mostly for surgical purposes and the signals are obtained by placing the electrodes directly within grey matter of the brain. Whereas partially-invasive BCIs connect the electrodes inside the brain, but the rest of the components are placed outside.

The main concern of any Brain-Computer Interface system is to accurately and precisely acquire activity pattern from the neural signals generating in the brain which can be converted to control signals. In any signal acquisition process, some unwanted signals or noise are bound to get incorporated with the desired signal and elimination of these noises is a must. This can be achieved by preprocessing these signals using different filters. After this the signal has to undergo few steps i.e. through the different components of the BCI system (Figure 1). BCI systems have three major components viz. Feature Extraction (Wolpaw, J.*et al.*, 2011), Feature selection (Garrett, D.*et al.*, 2003) and classification (Hinterberger, T.*et al.*, 2003). After preprocessing, the signals are needed to be further processed in order to extract the portions of interest from the entire signal. These portions are known as features. Several algorithms are available to extract the relevant features from the entire dataset. This extraction process can be performed in various domain like spatial domain (e.g. Common Spatial Patterns (Townsend, G.*et al.*, 2006)), non-linear domain (e.g. Fractal Dimensions (Boostani, R., 2004), Approximate Entropy (Wang, L.*et al.*, 2007)), time domain (e.g. Hjorth parameter (Lee, H.*et al.*, 2002), Auto-regressive parameter (Nakayama, K.*et al.*, 2006), frequency domain (e.g. Power Spectral Density Estimates (Bhattacharyya, S., 2010)) and time-frequency domain (e.g. Wavelet Transforms (Wang, Y.*et al.*, 2014)). In some cases, the dimension of the extracted feature vector may be very large and contain irrelevant features along with relevant ones. These unwanted features may even affect the performance of the classification algorithm and the final output of the entire system. In order to eliminate these, the feature selection step is required. Some of the algorithms which are used most often for selecting the most relevant features from the entire feature space are Independent Component Analysis (ICA) (Ekenel, H. K.*et al.*, 2004), Maximum Relevance Minimum Redundancy (mRmR) (Saeys, Y.*et al.*, 2007), Principal Component Analysis (PCA) (Rocchi,

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