Chapter 18
Design of Assistive Speller Machine Based on Brain Computer Interfacing

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ABSTRACT

Machine Learning (ML) has assumed a central role in data assimilation and data analysis in the last decade. Many methods exist that cater to the different kinds of data centric applications in terms of complexity and domain. Machine Learning methods have been derived from classical Artificial Intelligence (AI) models but are a lot more reliant on statistical methods. However, ML is a lot broader than inferential statistics. Recent advances in computational neuroscience has identified Electroencephalography (EEG) based Brain Computer Interface (BCI) as one of the key agents for a variety of medical and nonmedical applications. However, efficiency in analysing EEG signals is tremendously difficult to achieve because of three reasons: size of data, extent of computation and poor spatial resolution. The book chapter discusses the Machine Learning based methods employed by the author to classify EEG signals for potentials observed based on varying levels of a subject's attention, measured using a NeuroSky Mindwave Mobile. It reports challenges faced in developing BCIs based on available hardware, signal processing methods and classification methods.

1. INTRODUCTION

A *Brain Computer Interface* (BCI) is any system that does not rely on the conventional communication routines for a user to interact with a computer such as a mouse, keyboard, touchpad, etc. Instead, it utilizes signals from the brain to control a computer. Based on an imagined action, thought, or perception, signals are generated in specific regions of the brain and in turn, these signals may be used to control computers. Consequently, a BCI does not require physical motion of a user. The primary goal of any BCI, hence, is to provide an appropriate control interface, without requiring the usual communication

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pathways, such as gestures, voice, button clicks, etc.; the patient is required to be still, relaxed, and focussed on a single mental task, or a series of mental tasks.

In the recent years, hype has surrounded the study of Brain Computer Interfaces as its indispensable usefulness in many scenarios opens up a world of possibilities: many users are unable to communicate with people, or with computers due to various physiological conditions, such as amyotrophic lateral sclerosis (ALS), locked-in syndrome (LIS) or severe paralysis. For them, life becomes a burden; the inability to communicate and convey one's wishes to others is extremely daunting. BCI poses numerous solutions that may allow them to live better lives and communicate effectively. Over the past decade, scientists have developed voice translators that can translate thoughts to speech, wheelchairs, exoskeletons and games that work on the basis of imagined motion, amongst many other things. Such developments are on the rise and show promise to provide for better communication mechanisms in people who are unable to communicate.

Among the possible methods of acquiring signals from the brain are electroencephalography (EEG), magnetoencephalography (MEG) and functional magnetic resonance imaging (fMRI). The most popular signal acquiring method for Brain Computer Interfaces in use today is EEG, primarily due to its low cost, ease of setup and good temporal resolution; in contrast, MEG and fMRI are relatively expensive to setup, and are primarily used for medical research and diagnosis but this does not undermine their potential as acquisition systems for BCIs. The origin of the word *electroencephalography* is as follows: *electro*: denoting the electrical signals, *encephalo*: which refers to a phenomenon of the brain, and *graphy*: which denotes a drawing or a representation of a quantifiable phenomenon. EEG was discovered by Richard Canton (1842–1926). He experimented on rabbits and monkeys, and presented his findings of electrical activities of their brains. The first EEG recording of a human was presented by Hans Berger in 1942. EEG has seen innumerable uses in medical science, and researchers have tried to use EEG to understand the roots of epileptic seizures, analyse comas, etc. As an EEG recording would reflect the mental state of a subject, the EEG of a subject is altered by neurological conditions, disorders, drowsiness, drug actions, etc. EEG, due to its low cost, is also popular in numerous non-medical applications (a BCI is generally a non-medical application).

It is but natural for the reader to ponder that just like all other biological traits, even the electrical activity in the brain must be unique to each individual. Such is the case, and for a system to discern intentions from different brain signals of different subjects, Machine Learning (ML) techniques are employed. Machine Learning has its roots in classical Artificial Intelligence (AI) approaches, where the goal is to make a computer learn trends and discerning features in data (one of the prime differences between AI and ML is that AI generally refers to a replication of human abilities, whereas ML is used in data analytics across a broad spectrum of domains). However, ML techniques are more reliant on statistical measures. In a typical BCI setup, data corresponding to different *intentions* for each subject is collected several times, over multiple recording sessions. The author defines *intention* or *intent* in the current context to be any action that the user of a BCI would want the computer to perform, corresponding to a single and unique mental state. This will be further explained later in this section. The duration of each recording session is specific to each application. Once an adequate amount of data is collected for each intention, appropriate signal processing and machine learning approaches are used to teach the system the characteristics of the signals corresponding to each intention. In this chapter, the signal processing techniques that are featured are the *Wavelet Transform*, and *Common Spatial Patterns* (CSP). The Wavelet Transform essentially finds regions of maximum correlation of a signal to a wavelet, which is a small wave; the CSP algorithm is used to find spatial patterns in the processed data after the Wavelet Transform.