Chapter 79
A Review of Current Approaches of Brain Computer Interfaces

Lochi Yu
Escuela de Ingenieria Electrica, Universidad de Costa Rica, San Pedro, San Jose, Costa Rica

Cristian Ureña
Escuela de Ingenieria Electrica, Universidad de Costa Rica, San Pedro, San Jose, Costa Rica

ABSTRACT

Since the first recordings of brain electrical activity more than 100 years ago remarkable contributions have been done to understand the brain functionality and its interaction with environment. Regardless of the nature of the brain-computer interface BCI, a world of opportunities and possibilities has been opened not only for people with severe disabilities but also for those who are pursuing innovative human interfaces. Deeper understanding of the EEG signals along with refined technologies for its recording is helping to improve the performance of EEG based BCIs. Better processing and features extraction methods, like Independent Component Analysis (ICA) and Wavelet Transform (WT) respectively, are giving promising results that need to be explored. Different types of classifiers and combination of them have been used on EEG BCIs. Linear, neural and nonlinear Bayesian have been the most used classifiers providing accuracies ranges between 60% and 90%. Some demand more computational resources like Support Vector Machines (SVM) classifiers but give good generality. Linear Discriminant Analysis (LDA) classifiers provide poor generality but low computational resources, making them optimal for some real time BCIs. Better classifiers must be developed to tackle the large patterns variability across different subjects by using every available resource, method or technology.

INTRODUCTION

Brain-Computer Interfaces known as BCIs are systems that make possible a different approach of interaction in people's life. By properly interpreting brain signals it is feasible to control external devices such as computers, robots, neural prosthesis or even a "mental typewriter"(Blankertz, 2006). Most of them execute basic cognitive tasks compared to a standard interface (e.g. scroll up or down the mouse). However it is still a big challenge to develop a reliable, comfortable and friendly system to help people with physical disabilities, such as quadraplejic patients or patients

DOI: 10.4018/978-1-4666-4422-9.ch079

with amyotrophic lateral sclerosis (ALS)(DReed). Nowadays, video game and virtual navigation companies are encouraging BCI research to deliver innovative technologies. BCIs are even been used to improve memory, concentration and learning in general by modulating mu rhythms (Pineda, Silverman, Vankov, & Hestenes, 2003) for movements controls and improve the classification accuracy by practicing concentration procedures (Mahmoudi, & Erfanian, 2006).

This review will address current research in Brain Computer Interfases, their components, and the cutting-edge algorithms that run them. The most proven processing signal algorithms will be suggested in order to improve its temporal resolution and tackle its poor spatial resolution. Instead of digging on the nonstationarity characteristic of the EEG signals, it will use the most known neuromechanism or signature such as sensorimotor activity, P300 (Hoffmann, 2008)(Allison, & Pineda, 2003) and visual evoked potential (Gao et al., 2003). The electrophysiological activity mentioned above will be used in such BCI.

BCI BASICS

Background

Before refers to the concept of BCI as conceived currently, it is important to mention the origins of EEG. The first references about brain electrical activity recording go back to 1875 taken from the cortical surface in animals (Canton, 1875) and 1933 taken from the human scalp (Berger, 1993). Thanks to these two remarkable historic events, BCI found its origins by 1970 decade when it was possible to detect and classify some evoked responses known as epochs (Vidal, 1977). Early work involved a lot of experimentation with monkeys using invasive methods to acquire the EEG signals. Important neural activity in their motor cortex area was found when they accomplished several tasks stimulated by rewards.

During these years, many research teams were established to work on this field and trying to understand BCI nature using cognitive neuroscience, computing and mathematical models, or a combination of them. Several research projects were supported in improving signals quality, acquisition methods (invasive and non-invasive), temporal and spatial resolution and classification algorithms. As early state-of-art work, it was developed by 1991 one of the first EEG BCIs able to provide a sort of cursor control over a video screen (Wolpaw, McFarland, Neat, & Forneris, 1991).

However, the main achievements have been done during the last 15 years. Innumerable research results have been published since then, making its tracking almost impossible. Uncountable are the contributions from different areas such as materials science, digital signal processing, machine learning, electronics, computing, medicine as many others. All of them have contributed to the relative success of the BCIs up to today, creating a complete field for research.

Model

Currently, there is no standard model to represent a BCI as itself. All of them have things in common but they differ in the final application or need. As mentioned before, this review will be focused on non-invasive BCI by using EEG signals. Invasive BCIs has played a remarkable role in this field providing surpassing spacial and temporal neural information. It was found in the 70s that the monkeys were able to modulate voluntarily their firing rates of multiple neurons by implanting microelectrodes in the motor cortex (Fetz, 1969; Schmidt, McIntosh, Durelli, & Bak, 1978). Nonetheless, invasive methods are targeting more on sight recovery and providing new functionality for people with severe paralysis. Studies in blind patients and their visual cortex stimuli functionality have been done since decades ago (Brindley, & Lewin, 1968), nowadays it has allowed to few private companies deliver-