Chapter 16
Classification of EEG Signals for Motor Imagery Based on Mutual Information and Adaptive Neuro Fuzzy Inference System

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ABSTRACT

Electroencephalogram (EEG) signals based Brain Computer Interface (BCI) is employed to help disabled people to interact better with the environment. EEG signals are recorded through BCI system to translate it to control commands. There are a large body of literature targeting EEG feature extraction and classification for Motor Imagery tasks. Motor imagery task have several features can be extracted to use in classification. However, using more features consume running time and using irrelevant and redundant features affect the performance of the used classifier. This paper is dedicated to extracting the best feature vector for motor imagery task. This work suggests two feature selection methods based on Mutual Information (MI) including Minimum Redundancy Maximal Relevance (MRMR) and maximal Relevance (MaxRel). Adaptive Neuro Fuzzy Inference System (ANFIS) classifier with Subtractive clustering method is utilized for EEG signals classifications. The suggested methods are applied to BCI Competition III dataset IVa and IVb and BCI Competition II dataset III.

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1. INTRODUCTION

BCI (Hassanien et al., 2015) system is allowed people to control different applications and devices in real time by decoding brain electrical activity to action (Azar et al., 2014). This electrical activity is generated by billions of neurons and EEG is able to measure the combination of these electrical activities. BCI system does not base on normal brain signal pathway for peripherals and muscles but it is enabled users to connect with the environment through his/her thoughts. In addition, BCI system is employed to recording brain signals by EEG through electrodes attached to the scalp. EEG signals based BCI is used to facilitate communication between peoples and computer especially people who are totally paralyzed e.g: Amyotrophic lateral sclerosis (ALS) or spinal injuries. Moreover, EEG is employed to aid locked in patients to express their needs to caregivers (Wolpaw et al., 2002). Furthermore, EEG signals are non-stationary and it is commonly used in non-invasive (Millan et al., 2004) BCI.

EEG signals are captured either by invasive BCI (Odoherty et al., 2009) or semi-invasive (Birbaumer, 2006) BCI or non-invasive BCI (Millan et al., 2004). In Invasive BCI microelectrodes are implanted inside the brain through surgery and it produces signals with high quality. However, over time it is prone to scar tissue. With regard to semi invasive, BCI electrodes are implanted underneath the skull over the cortex and it uses Electrocardiography (ECoG) to record electrical brain signals. On the other hand, non-invasive BCI is used to record brain signals through electrodes over the scalp in certain location. In addition, it is recorded by many techniques such as functional Magnetic Resonance Imaging (fMRI) (Weiskopf et al., 2007), Magnetoencephalography (MEG) (Ioannides, 2006), Positron Emission Tomography (PET) (Ollinger et al., 1997) and electroencephalography (EEG) (Teplan, 2002). However, EEG is the most commonly used for BCI for the sake of low price devices.

There are two approaches for BCI (Lehtonen, 2002) which are pattern recognition approach and operant conditioning approach. In pattern recognition: different EEG rhythms are produced through mental tasks in which it activates different cortical areas of the brain. These mental tasks include motor imagery tasks, visual tasks, arithmetic tasks and baseline tasks. Therefore, different areas of the brain are activated according to the mental task. For instance, right cortex area of the brain is activated for left hand or foot imagination movements. Furthermore, right hand or foot imagination movement activates the left cortex area of the brain. In addition, the arithmetic tasks have to activate the prefrontal area of the brain and the visual tasks should activate visual collectivity region.

In operant conditioning approach: BCI system is based on self-organizing of different kinds of EEG rhythms and event related potentials. For operant conditioning, the users do not conscious of any type of EEG rhythms except if they receive feedback. Thereafter, training feedback is an important step to the user to control BCI reaction. In addition, self-organizing learning of EEG response (Kubler et al., 2001) is based on getting the feedback for the EEG task in real time and building up correct behavior.

BCI system works in two modes included synchronous and asynchronous (Townsend et al., 2004; Lehtonen, 2002). For synchronous BCI mode, classification and analyzing EEG data is controlled by predefined time window i.e., the system initiates the period of control. However, EEG data in asynchronous BCI mode is analyzed and classified continuously i.e., the user initiates mental tasks of control.

The steps carried out for EEG signal analysis consist of four major phases which are signal acquisition, signal preprocessing, feature extraction, and classification. In signal acquisition phase, brain signals are recorded through electrodes attached to EEG cap. In pre-processing phase, EEG data is filtered using filtering methods such as Laplacian Spatial Filtering (LSF) (Qin et al., 2005) to remove data noise. In feature extraction phase, brain signals features are extracted in which it is used to differentiate between

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