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**CLASSIFICATION OF
EEG BASED TASK ON COLOUR VISUALIZATION
AND COLOUR IMAGERY**

by

**DIVAKAR PURUSHOTHAMAN
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A thesis submitted in fulfillment of the requirements for the degree of
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LIST OF ABBREVIATION

ANN	Artificial Neural Network
ACS	Augmented Cognition System
ALS	Amyotrophic Lateral Sclerosis
All-subjects	All subjects Combination
BGN	Bayesian Graphical Network
BCI	Brain Computer Interface
BMI	Brain Machine Interface
BP	Backpropagation
BQM	Bayes Quadratic Model
CFMA	Channel-Frequency Map Analysis
CICA	Constrained Independent Component Analysis
CIT	Colour Imagery Task
CVT	Colour Visualization Task
DAP	Data Acquisition Protocol
EEG	Electroencephalography
ERP	Event Related Potentials
FBCSP	Filter Bank Common Spatial Pattern
FCA	Fuzzy Clustering Algorithm
FFT	Fast Fourier Transform
FFNN	Feedforward Neural Network
FLC	Fisher Linear Classifier
GA	Genetic Algorithm
GMM	Gaussian Mixture Model
GUI	Graphical User Interface
HMM	Hidden Markov Model
KNN	K Nearest Neighbourhood
LDA	Linear Discriminant Analysis
LDC	Live Data Capture
LCD	Liquid Crystal Display
Max%	Maximum Mean Classification Accuracy
MIMM	Mutual Information Maximization Method

MLP	Multilayer perceptron
NN	Neural Network
PCA	Principal Component Analysis
PNN	Probabilistic Neural Network
PSD	Power Spectral Density
PWC	Parzen Window Classifier
SCP	Slow Cortical Potentials
SEF	Spectral Energy Feature
SENF	Spectral Entropy Feature
SEENF	Spectral Energy Entropy Feature
SFAA	Single Feature Accuracy Analysis
SSVEP	Steady State Visually Evoked Potentials
SVM	Support Vector Machine
TEF	Temporal Energy Feature
TENF	Temporal Entropy Feature
TEENF	Temporal Energy Entropy Feature
TTD	Thought Translation Device
VEP	Visually Evoked Potentials

PENGGELASAN TUGAS BERASASKAN EEG ATAS VISUALISASI WARNA DAN BAYANGAN WARNA

ABSTRAK

Electroencephalography (EEG) adalah satu ukuran gelombang otak yang digunakan untuk memantau keadaan kesihatan pesakit dalam aplikasi perubatan dan bidang penyelidikan yang lain. Isyarat EEG juga digunakan untuk membangunkan sistem pengantara mesin otak (BMI). BMI membantu untuk membawa niat pengguna dan ia adalah sistem perantaraan bijak yang bertindak sebagai saluran komunikasi untuk menghantar mesej kepada seluruh dunia luar. Ia merupakan salah satu pendekatan komunikasi yang paling efisien bagi orang-orang yang berbeza keupayaan. Sejak dua dekad yang lalu, ramai penyelidik telah tertumpu kepada pembangunan BMI yang sesuai menggunakan pelbagai isyarat EEG seperti potensi perlahan kortikal, P300 potensi, potensi dibangkitkan visual dan potensi peristiwa yang berkaitan. Tesis ini membincangkan perkembangan persepsi warna berdasarkan BMI menggunakan kaedah bukan invasif untuk orang yang berbeza keupayaan. Dua protokol yang menggunakan visualisasi dan imaginasi warna yang berbeza telah dikaji. Data EEG dikumpulkan daripada sepuluh subjek yang menggunakan mindset-24 EEG perolehan data instrumen dengan 19 saluran topi susunan elektrod. Data diproses dan ciri-ciri yang diekstrak dari data EEG dirakamkan. Set ciri yang diekstrak kemudian dimasukkan kepada rangkaian saraf tiruan untuk mengklasifikasikan tugas-tugas yang berbeza. Daripada keputusan klasifikasi, tenaga ciri entropi spektrum yang menggunakan rangkaian neural mempunyai berkebarangkalian prestasi pengelasan yang tertinggi. Dalam isyarat EEG, jalur frekuensi dan pemilihan saluran memainkan peranan yang penting dalam meningkatkan prestasi klasifikasi dan mengurangkan bilangan ciri-ciri input. Dalam penyelidikan ini, jalur frekuensi dan saluran algoritma pemilihan dicadangkan untuk mencari jalur frekuensi yang berkaitan dan kedudukan elektrod (atau saluran) untuk protokol BMI yang dicadangkan. Keputusan ujikaji menunjukkan kombinasi jalur frekuensi alfa, beta dan gamma ($\alpha\beta\gamma$) memberikan ketepatan pengelasan yang lebih baik dan 9 saluran yang menggunakan hasil algoritma pemilihan klasifikasi ketepatan yang lebih baik melebihi 90% jika dibandingkan dengan kaedah konvensional.

CLASSIFICATION OF EEG BASED TASK ON COLOUR VISUALIZATION AND COLOUR IMAGERY

ABSTRACT

Electroencephalography (EEG) is a measure of brain waves used to monitor the state of health of the patients in medical applications and other research areas. EEG signals are also used to develop Brain Machine Interface (BMI) system. BMI helps to bring out the intention of users and it is an intelligent interfacing system which acts as a communication channel for sending messages to command the external world. It is one of the most promising communication approach for the differentially enabled people. Over the past two decades, many researchers have concentrated on developing a suitable BMI using variety of EEG signals such as slow cortical potentials, P300 potentials, visually evoked potentials and event related potentials. This thesis discusses the development of colour perception based BMI using non invasive method for the differentially enabled people. Two protocols using visualization and imagination of different colours were investigated. The EEG data was collected from ten subjects using mindset-24 EEG data acquisition instrument with 19 channel electrode cap arrangement. The data is preprocessed and features are extracted from the recorded EEG data. The extracted feature set is then fed to a neural network model to classify the different tasks. From the observed classification results, the spectral energy entropy features using probabilistic neural network has the highest classification performances. In EEG signals, frequency band and channel selection plays an important role in increasing the classification performance and in decreasing the number of input features. In this research work, frequency band and channel selection algorithm is proposed to find the relevant frequency bands and electrode positions (or channel) for the proposed BMI protocols. Experimental results show that the alpha, beta and gamma ($\alpha\beta\gamma$) frequency band combinations gives better classification accuracy and the selected 9 channels using the proposed channel selection algorithm yields a better classification accuracy of above 90% when compared to the conventional method.

CHAPTER 1

INTRODUCTION

This chapter focuses on the development of Brain Machine Interface (BMI) systems that can be used as a assistive device for the differentially enabled community. This chapter also deals with the objectives of the proposed research along with the organization of the thesis.

1.1 Overview

Electroencephalography (EEG) is defined as a measure of electrical activity recorded from the brain using electrodes (Teplan, 2002). EEG signals (or brain signals) indicate the mental state of the brain and these evoked signals can be used to control external devices. EEG signals can be recorded using invasive, semi invasive and non-invasive methods. Non-invasive method is the safest and they offer significant benefits with no surgical risks. EEG signals are widely used for clinical purposes such as monitoring patient health, diagnosing mental disorders and evaluating the effects of smoking, drinking (alcohols) and drugs. EEG signals can be used in BMI based communication systems and also in lie detection and biometric developing systems (Wiki_BCI, 2011; Farwell et al., 1991).

BMI is an interfacing system that provides a communication link between the human brain and a digital computer using EEG signals (Wolpaw et al., 2004). BMI aims to develop a communication system for the people who are paralyzed (or differentially enabled) and suffering with severe neuromuscular disorders such as quadriplegics,

amyotrophic lateral sclerosis (ALS), brainstem stroke, and spinal cord injury. Using BMI, the thought-controlled EEG signals can drive computers directly rather than controlling them by physical means.

Starting from 1970's, in BMI research, various approaches has been developed for recording the EEG signals. Initially, BMI researchers used implanted (or invasive) electrodes on monkey. Later, they implanted electrodes on human to control computer cursors, TV operations and robotic arms (Kennedy et al., 2000; Wiki_BCI, 2011). Over the past few decades, many researches have developed BMI systems with implanted electrodes. Nowadays, the scalp electrodes are widely used and it overcomes the problem in using implanted electrodes such as inconvenience and the need of specialist in implanting electrodes without harming the brain (Kennedy et al., 2000). Previous research works also indicate the numerous advancements that have occurred in the past two decades on developing a BMI using various types of EEG signals such as visual evoked potential (VEP), slow cortical potential (SCP), P300 evoked potential, sensorimotor activity and mental tasks (Wolpaw et al., 2000; Wolpaw et al., 2004; Vaughan et al., 2003; Bashashati et al., 2007). All these BMI methods provide an alternative communication mode for people having movement disorders. However, users require adequate training to control the BMI system and can able to perform maximum of five control actions (or tasks). The increase in number of control actions in BMI lead to decrease in classification performance (Li et al., 2007). Hence, in order to develop a simple and universal BMI system which works without any training and also has more number of control actions without decreasing the performance, BMI system based on colour perception has been formulated.

The aim of this research work is to develop a BMI system using colour perception, which is relatively new in BMI research. Authors Tripathy et al., have investigated the effect of different colours on the EEG signal while visualizing and analyzed whether different colours affect the behavior of EEG signals (Tripathy et al., 2006). Using this theoretical concept of colour perception, the BMI using colour visualization task (CVT) and colour imagery task (CIT) have been proposed and analyzed to help the differentially enabled community. CVT uses the visualization of colours and CIT uses the imagination of colours in a relaxed condition. The effectiveness of the proposed two methods was analyzed using different features and neural network models. Moreover, in BMI applications, a large number of frequency bands and channels are used and they lead to increase in number of input features which in turn increases the complexity of the system. Hence, to minimize the number input features and to enhance the BMI performance, frequency band selection using combination method and channel selection using statistical approach were analyzed and has been discussed in this research work.

1.2 Problem Statement and Significance of the Study

People normally can communicate their thoughts through speech. People with severe hearing impairment, voice impairment and physical impairment require a suitable medium to communicate. Severe hearing and voice impaired people are able to convey their thoughts through gesture signs and facial expressions. However, people who are physically impaired severely cannot show any expressions using their hands or face. But they are mentally able and can communicate through their brain signals using BMI. In the past two decades, several research works were done in the area of BMI using different EEG signals. Researchers have analyzed the EEG signals based on

parametric and non-parametric feature extraction methods, time domain analysis, frequency domain analysis and time frequency analysis (Wolpaw et al., 2000; Wolpaw et al., 2004; Vaughan et al., 2003; Bashashati et al., 2007).

Most of the researches on BMI are carried out using both invasive and non-invasive method. But non-invasive method is the safest one and more protective way of developing BMI. Previous research works on BMI indicates that the performances of a BMI system is gradually reduced when the number of tasks is increased (Li et al., 2007; Wolpaw et al., 2004; Gupta et al., 2009). In this thesis, non-invasive BMI system based on CVT and CIT are developed using visualization and imagination of different colours. The number of tasks is also increased to eight. These protocols were developed in such a way, that the subject is in relaxed mental state and free from medication during the entire data collection. In BMI applications, the number of input features are normally high due to presence of a large number of scalp electrodes (or channels) and frequency bands. To minimize the number of input features and to find the relevant frequency bands and channels, frequency band and channel selection method were proposed in this research.

1.3 Research Objectives

The purpose of this research is to develop a simple BMI system using colour perception for the differentially enabled community. The objectives of this research are described below:

i. To develop a protocol for the data collection using non-invasive method

The BMI using invasive method involves implanted electrodes which is very risky, may leads to brain injury and cause discomfort in usage. Also, it is expensive and requires certified experts to implant the electrodes. The non-invasive method uses scalp electrodes which is user-friendly in handling and does not need an expert. The data collection protocol must be simple and trouble-free for the users as the BMI involves mental works. In this research work, simple protocols are to be formulated to record the EEG signals emanated from the subjects while performing CVTs and CITs.

ii. To select suitable features and neural classifiers for BMI system

In order to extract the salient features which provide better classification performance of above 80%, suitable feature extraction algorithms and neural network classifiers have to be proposed for these CVTs and CITs.

iii. To select the essential frequency band combination for the BMI

EEG signals involve five different frequency bands namely delta, theta, alpha, beta and gamma, each band plays a vital role in the development of BMI. Most of researchers have adopted all the five frequency bands which in turn lead to an increase in the number of input features. In order to find the important bands and reduce the number of input features while developing a neural network model, it is proposed to develop simple algorithms.

iv. To select the number of EEG channels required for the BMI

Maximum of 19 channels are required to collect EEG signal based on 10/20 international standards. More number of channels increases the number of input features. Further, information from irrelevant channels leads to poor performance. Hence, to reduce the number of input features, it is required to develop appropriate channel selection algorithm.

1.4 Scopes of work

The scope of this work is to develop a suitable Brain Machine Interface (BMI) system for the differentially enabled people (aged 21 to 25 years). To provide a better communication system for them, colour perception based BMI system is designed in this work. In this research work, EEG signals are collected and analyzed using two protocols such as colour visualization (CVT) and colour imagery tasks (CIT) which are carried out to develop a suitable BMI system.

The EEG signal will be analyzed through implementation of feature extraction methods and artificial intelligences techniques. In order to improve the quality of the EEG signal, digital signal processing techniques such as segmentation, overlapping and filtering are applied on the signal before feature extraction process. In this CVT and CIT based BMI system, the relevant channels and frequency bands are identified in the collected EEG signals; in order to reduce the number of input features and to enhance the classification performance.