CLASSIFICATION OF ELECTROENCEPHALOGRAPHY SIGNAL USING STATISTICAL FEATURES AND REGRESSION CLASSIFIER

NURBAITY BINTI SABRI

UNIVERSITI TEKNOLOGI MALAYSIA

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With love and gratitude to Allah, my beloved husband and family

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ABSTRACT

Enormous digital electroencephalography (EEG) acquisition systems available nowadays for researchers due to the high demand in the brain signal research. Using EEG-based emotion recognition, the computer can look inside a user head to observe their mental state of sad and happy emotion. Thus, there is a need for efficient mechanism to detect those emotions accurately along with computation complexity. The current algorithms available are excessively complex with higher computational time. In this study, 14 channels of EEG signals acquired from emotive device with 128 Hz sample rate. These raw signals undergo preprocess stage using band pass and ICA filter. This research focuses two components which is feature extraction and classification. A combination of statistical features has been carrying out to extract important signal. To classify the EEG signal into sad and happy classes, Support Vector Machine (SVM) and Linear Regression has been applied. Waikato Environment for Knowledge Analysis (WEKA) as training tools is employ to train the dataset and test the accuracy of the classifier. Results presented that Linear Regression has better detection accuracy with 95% compared to SVM with 80% average accuracy. In conclusion this research suggests using Linear Regression for future work on predicting between sad and happy emotion from the EEG signal.

ABSTRAK

Pelbagai alat pengesanisyarat elektroensefalografi “*Electroencephalograph*y” (EEG) berada dipasaran pada masa kini khusus untuk penyelidikan otak. Perkara ini berlaku disebabkan oleh permintaan yang tinggi didalam bidang kajian isyarat otak. Menggunakan EEG sebagai asas dalam kajian untuk mengenal pasti emosi, komputer digunakan untuk melihat kondisi otak dan mengenal pasti keadaan mental mereka. Justeru itu, mekanisma untuk mengenal pasti emosi secara tepat berserta dengan pengiraan yang ringkas dan mudah amat diperlukan. Algorithm yang ada sangat rumit dan tempoh pengiraan yang agak lama. Didalam kajian ini, 14 saluran isyarat EEG diperoleh daripada peralatan Emotiv beserta dengan 128Hz sample rate. Kesemua isyarat ini melalui fasa proses permulaan menggunakan penapis lulus jalur “*band pass*” dan penapis ICA. Kajian ini fokus kepada dua komponen iaitu pengekstrakan ciri-ciri dan pengkelasan. Kombinasi ciri-ciri statistik telah digunakan untuk mengekstrak isyarat yang penting. Alogritma Support Vector Machine (SVM) dan regresi linear telah digunakan telah digunakan untuk pengkelasan diantara emosi sedih dan gembira. Waikato Environment for Knowledge Analysis (WEKA) sebagai peralatan latihan juga telah diadaptasi untuk melatih data dan menguji ketepatan pengkelasan emosi. Keputusan menunjukkan bahawa regresi linear menghasilkan ketepatan yang lebih tinggi iaitu 95%, lebih tinggi daripada SVM iaitu hanya 80% purata ketepatan. Kesimpulan daripada kajian ini merumuskan bahawa penggunaan regresi linear untuk kerja-kerja berkaitan pengkelasan diantara emosi sedih dan gembira daripada isyarat EEG pada masa hadapan.

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LIST OF ABBREVIATIONS

AC	Accuracy
ARFF	Attribute Relation File Format
BPNN	Back-Propagate Neural Network
DC	Direct Current
EEG	Electroencephalogram
ENN	Elman Neural Network
FFT	Fast Fourier Transform
FIR	Impulse Response Filter
FMRI	Functional Magnetic Resonance Imaging
FN	False Negative
FP	False Positive
IADS	International Affective Digitized Sounds
IAPS	International Affective Picture System
ICA	Independent Component Analysis
IIR	Infinite Impulse Response Filter
KNN	K-Nearest Neighbour
LDA	Linear Discriminant Analysis
MEG	Magneto Encephalography
MFCC	Mel Frequency Cepstrat Coefficient
MLP	Multilayer Perceptron
MLPNN	Multilayer perceptron neural network
NN	Neural Network
NPV	Negative Predictive Value
PCA	Principle Component Analysis
PET	Positron Emission Tomography
PFC	Prefrontal cortex

PPV	Positive predictive value
PSD	Power Spectral Density
PSD	power spectral density
SVM	Support Vector Machine
TN	True Negative
TP	True positive
WEKA	Waikato Environment for Knowledge Analysis

CHAPTER 1

INTRODUCTION

1.1 Introduction

Brain is the one of important organ of human body which is capable to generate an electrical signal. Limbic system is a part of brain which plays primary role in setting a person’s emotional state. This particular part stores positive emotional memory as happy, optimistic, and honored etc. Melancholic, stress, sadness are categories and stored as negative memories. The PFC located at the front half of the brain responsible for emotional control, empathy, and judgment etc. If the PFC is low in activity, it can make a person disorganized or antisocial. On the other hand, if it is hyper active, it can cause anxiety, inflexibility and impulsiveness (Phelps, 2012) .

Emotions on the other hand become the most crucial part of neuroscience and understandings of brain part that trigger emotional process are of great importance for future research in human cognition associated with psychopathology (Jackson *et al.,* 2005; Ogino *et al.,* 2007; Spielberg *et al.,* 2008). The activation over the right PFC for negative or pain related trigger and left PFC for positive trigger has been observed through electroencephalography (EEG) (Aftanas *et al.,* 2001a, 2001b, 2002; Davidson *et al*., 1990; DePascalis *et al.,* 1998; Harmon-Jones and Allen, 1998; Tomarken *et al.,* 1990).

According to Soanes (2008), a brainwave can be defined as a sudden clever idea. Small pulses produce an electric activity when neurons communicate with each other. This wave changes according to human action and emotion where it reaches to high frequency when the brain is wired or hyper alert or vice versa when it is dreamy or feels tired (Roy *et al*., 2007). It is the second front studies in biological research. Hans Eysenck, the German-born British psychologist has used this brainwave to study pattern and speed of response in people taking intelligence tests. From the study, relationships between certain aspects of EEG waves are identified, for event-related-potential waves and scores on a standard psychometric test of intelligence (Sternberg, 2013).

The EEG waves are very important to investigate brainwave. Varieties of image acquisition machine are available to measure a brain activity such as EEG, magneto encephalography (MEG), positron emission tomography (PET), functional magnetic resonance imaging (fMRI), and optical imaging (Al-ani and Trad, 2010). Brain signal activity detected using EEG signal are widely used in medical science, neuron science, psychology, computer science, electric engineering and others (Heejun *et al*., 2013). EEG signal is commonly used due to certain state can be recognized from the psychoanalysis of brainwave balancing state (Hj Murat *et al*., 2010). The typical quantitative of brainwaves that taken into experiment is delta waves, theta waves, alpha waves and gamma waves. Each wave plays important roles in human activities such as dreamless sleep, creative, fantasy, relaxed, thinking, and alertness (Neurosky, 2009).

EEG is emerging rapidly over this decade. Research made by Hosseini *et al.*, (2011) have classified the emotional stress using brain activities into two categories which is calm-neutral and negative excited. It shows an improvement of accuracy by combining the EEG signal and peripheral signals. EEG brainwaves are used progressively in Intelligent Tutoring System (ITS) where the precision and objectivity of cognitive and emotional state are crucial to predict the learner's emotion (Heraz *et al*., 2007).

This research focuses on the features extraction techniques used to classify the EEG signals into two emotions sad and happy where “sad” represents the right PFC and “happy” represent left PFC. The accuracy is measured will be The obtained results are very important and useful for future research and application development in emotion fields.

1.2 Research Background

Brain is a complex organ in human body and it is still a mystery to human being (Eagleman, 2007). Understanding the basic fundamentals of the brain in terms of its physiology and functionality will be the key to solve many real world problems. Psychology is applied in order to solve problem in fields such as mental health, business, education, sports, law, medicine and the design of machines (psychology book). Affective information is collected from facial features and vocal patterns, which are the most widely studied modalities for affect detection (Tao and Tan, 2005). Besides these modalities, research has recently focused on the use of physiology signals to study emotion (Kim, *et. al*, 2008).

According to Dhariya, (2013) emotion is a vital aspect in a communication between human beings. Emotions are also considered to reconcile stimulus and response. However, it is very subjective and hard to define (Dhariya, 2013). Takahashi (2004) agreed that emotion recognition is very interesting fields; however it is difficult task to recognize emotions. Hosseini *et al.* (2011) have classified human emotion states with main focus on stress using EEG brain signals in order to assist computers and robot to communicate naturally with human. Classification process is important as it is one of the preliminary steps in order to develop a high-quality Business Computer Interface (BCI) application (Hosseini and Naghibi-S, 2011).

Selection of the finest frequency band and pull out a good set of features is still an unsolved research issue (Sridhar and Rao, 2012). There have been many researches carried out to find good features extraction. Features comparison between conventional features and new proposed energy based features has shown an increase in accuracy (Murugappan *et al*., 2010). More efficient features are needed to improve the accuracy of emotion detection.

Accuracy in pattern recognition of brainwave is important to classify the psychologist behavior of person in order to eliminate misinterpret data. Accurate data base is required in order to copy human communication. Several studies have been conducted to recognize emotions using face and voice. Huge success has been achieved using those signals. 60% of research is carrying out using EEG-based artificially evoked emotion (Bos, 2007) .

1.3 Problem statement

To extract information from EEG signal, classification of data with appropriate techniques is of great importance EEG signals carry valuable information about the function of the brain. The classification, features extraction and evaluation procedures of these signals have not been well developed (Kutlu *et al.*, 2009). Data itself plays an important role towards the accuracy of classification. It has been identified; two types of data can be extracted from the brain signal which is associated to frequency band (Murugappan *et al*., 2010) and time domain (Yuen *et al*., 2013). The analysis of brain signals using noninvasive technique is a challenging task and its solution depends on machine learning, signal processing and the knowledge of the neuroscience.

Nowadays, there is no easily available benchmark databases of EEG labeled with emotions. However, there are number of algorithms to recognize emotions such as machine learning, curve fitting, signal processing and many more. But the recognition accuracy is very low. Therefore development of algorithms is needed to improve the accuracy. As this field is still new, only limited emotions can be recognized (Liu, Sourina, and Nguyen, 2011).

The statistical approach shows an excellent result in EEG classification. Yuen *et al.*, (2014) have achieved overall classification rate as high as 90%. However, the proposed classification technique is complex and time consuming. Therefore to achieve high accuracy with more simple classification in less time is needed.

There are a number of researches conducted on feature extraction of EEG signals such as statistical features, signal variance, and power spectral density (PSD). But it stills an open research area and there are some issues need to be addressed such as:

i. How to achieve accuracy to differentiate sad and happy emotion?
ii. How to classify emotions into two classes?
iii. How much accuracy is achieved, and how the accuracy is properly evaluated?

1.4 Objectives

The main objective of this study is to classify the EEG signals according to emotion as sad or happy using statistical features extraction technique to improve the classification accuracy. The specific objectives are given as follows:

i. To adapt statistical features algorithm to classify EEG signal into sad and happy.
ii. To deploy classification algorithm on sad and happy emotion using the EEG signal.

1.5 Scope

The scopes of this research are as follow:

i. Data was conducted from 20 participants from Universiti Technologi Malaysia (UTM) age ranges between 25-35 years using Emotiv's Neuroheadset a signal acquisition device. This experiment has been supervised by PhD student.

ii. EEG signal recorded from emotive device will be classified into sad and happy emotion.

1.6 Research Overview

This research is divided into three chapters. Chapter 2 presents a background literature on emotion theories. This chapter includes reviews on emotion representations models and neuroscience environment. The feature extractions used by different researchers are also evaluated and presented. Classification technique to determine the emotions are reviewed to find the classification that suit with the proposed feature extraction. Chapter 3 describes methodology used to conduct present research work. The operational framework for the rest of research is also presented in this chapter. The selected features extractions and techniques for classification are presented in sequence. Chapter 4 explains the propose technique including feature extraction calculation, classification technique flow and the evaluation procedure to find the best classification for proposed feature extraction. The evaluation is determined based on TP, FP, accuracy and precision. Chapter 5 describes result, discussion, conclusion or outcome of the research project.

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