EEG-BASED EMOTION CLASSIFICATION USING WAVELET BASED FEATURES AND SUPPORT VECTOR MACHINE CLASSIFIER

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Every challenging works needs self-efforts as well as guidance of elders especially those who were very close to our heart. My humble effort I dedicated to my sweet and loving

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Whose affection, love, encouragement and prays of day and night make me able to get such success and honour

Along with all hardworking and respected

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ABSTRACT

As technology and the understanding of emotions are evolving, there are numerous opportunities for classification of emotion due to the high demand in the psychophysiological research. The researches need an efficient mechanism to recognise the various emotions precisely with less computation complexity. The current methods available are too complex with higher computational time. This study proposes a classification of human emotion using electroencephalogram signals (EEG). The study utilised electroencephalogram signals (EEG) to classify emotions which is positive/negative arousal, valence and normal emotions. Electroencephalogram signals (EEG) are analysed from 4 different participants from the dataset that acquire from the public data source. These dataset go through several processes before the derivation of the features such as preprocessing using band pass filtering and artifacts removals, segmentation of the signals and Multiwavelet Transform (MWT) analysis of the processed data. The signals are decomposed up to level 3 decomposition and detail coefficients are used for features extraction. Statistical and power spectral density (PSD) features are computed and feed into the classifiers. Simple classification methods Support Vector Machine (SVM) is used to classify the emotion and their performances are evaluated. The experimental results report that statistical features and Support Vector Machine (SVM) achieved better accuracy up to 75.8%, 72.3% and 74.0% for arousal, valence and normal class respectively. In conclusion this research suggests the use of Multiwavelet Analysis for future work on recognizing various emotions from the Electroencephalogram signals (EEG).

ABSTRAK

Sejajar dengan perkembangan teknologi dan pemahaman emosi, terdapat banyak peluang terbuka untuk kajian berkaitan klasifikasi emosi yang disebabkan oleh permintaan yang tinggi dalam bidang penyelidikan psychophysiologi. Kajian tersebut memerlukan mekanisme yang lebih kukuh dan cekap dalam mengenalpasti pelbagai bentuk emosi dengan tepat dengan penggunaan masa pengiraan yang singkat. Kaedah yang sedia ada terlalu rumit dan kompleks di mana masa pengiraan yang diperlukan adalah lebih panjang. Kajian ini mencadangkan pengelasan emosi manusia menggunakan isyarat Electroencephalogram (EEG). Kajian ini adalah bertujuan untuk mengklasifikasikan dua emosi iaitu negatif/positif *arousal*, *valence* dan *normal*. Isyarat Electroencephalogram (EEG) ini dianalisis daripada 4 peserta yang berbeza dari dataset yang diperolehi daripada sumber data yang dikenalpasti. Dataset ini melalui beberapa proses sebelum pengekstrakan ciri seperti pra pemprosesan yang menggunakan band pass filtering dan penyingkiran artifak, segmentasi isyarat dan analisis data yang telah diproses menggunakan Multiwavelet Transform (MWT). Isyarat itu akan diurai sehingga tahap ke 3 penguraian dan pekali yang dipilih akan digunakan untuk pengekstrakan ciri di mana data statistik dan power spectral density (PSD) dikira dan digunakan sebagai input kepada sistem pengelasan. Kaedah klasifikasi mudah iaitu Support Vector Machine (SVM) digunakan untuk mengklasifikasikan emosi dan prestasi eksperiment ini dinilai. Keputusan eksperimen melaporkan bahawa ciri statistik dan Support Vector Machine (SVM) telah mencapai ketepatan yang lebih baik sehingga 75.8%, 72.3% dan 74.0% bagi *arousal*, *valence* dan *normal*. Kesimpulannya kajian ini mencadangkan penggunaan Analisis Multiwavelet untuk penyelidikan di masa depan dalam mengenalpasti pelbagai emosi dari isyarat Electroencephalogram (EEG).

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CHAPTER 1

INTRODUCTION

1.1 Introduction

The word 'emotion' has a very complex and vast definition yet it has a broader meaning than feelings. The definition of emotion can be define as a complex set of interactions between the subjective and objective in which intermediated by neural and hormonal systems (Kleinginna Jr & Kleinginna, 1981). Each individual has their own emotions. There are many types of basic human emotions that often felt by human. Examples of basic human emotions are happy, sympathy, shame, sadness, anger and fear.

There are three types of emotional aspects which are physiological arousal, expressive behaviour, and cognitive appraisal. Cognitive appraisal can be described with words, expressive behaviour can be seen clearly from the facial expression, body language, posture, and finally physiological arousal specifically involved brain activity, body temperature and heart rate (Cohn, 2007). It is merely expressive behaviour aspects can be seen clearly while the other two aspects are intangibles.

Emotional intelligence as a subset of knowledge in the discipline of computer is still at state-of-the-art. However, emotions or feelings as one of the elements that are found in humans were studied for hundreds of years. Human emotion is not only a subject of study and experiment for clinical and psychological purposes but it is also seen in a variety of social science perspectives and humanities such as sociology, geography, education, linguistics, history and so on.

The relationship between the emotions and brain are closely connected in function where they mutually control each other. Part of the brain that responsible for emotions is called the limbic system. Human brain consists of billions brain cells called neurons that communicate with each other by emitting an electric wave. These electrical waves produced by neurons in the brain are called "brain waves" which is an "electric current". When the brain can no longer produce the brain waves, then it is identified that the brain is dead. These brain waves can be measured with electroencephalograph (EEG) instruments.

Electroencephalogram signals (EEG) is bioelectrical signal from the electrical activity in the cortex or surface of the scalp, which is due to the physiological activity of the brain (Teplan, 2002). An enormous amount of research work has been focussed towards the introduction and use of information from human emotions. One of the classifications methods of human emotion is the study of brain wave pattern where the information is deriving from the use electroencephalogram. Other methods in emotion classification including emotional face recognition vision system, respiratory rate and tone of the human voice recognition.

The study and exploration of brain waves have exploiting various signal processing and artificial intelligence skills in the effort to develop and improve emotions classification. The discovery of the study will be used to develop a system that will facilitate the interaction between human and computer and expand the use of smart technology in various machines such as robots that lead to various intelligence systems and machines.

The currently available research in Emotion Classification is Feature Extraction using wavelet analysis from electroencephalogram signals (EEG) in which the signals are decomposed into five different frequency sub-bands before the commence of the extraction task. The proposed features that have been extracted are used as a classification input and the selection of suitable classifier will produce a significant accuracy (Singh, Singh, & Gangwar, 2013). The application of Back-propagation neural network to classify five types of emotions: Anger, Sad, Surprise, Happy, and Neutral achieved the highest success rate as 95% of correct classification (Yuen, San, Seong, & Rizon, 2011). There is study that developed emotion recognition system using discrete wavelet transforms (DWT) features extraction with two common classification methods i.e. K-Nearest Neighbour (KNN) and Linear Discriminant Analysis (LDA) used for classifying basic emotion. In the study, the maximum average classification rates achieved are 83.26% and 75.21% for KNN and LDA respectively (Murugappan, Ramachandran, & Sazali, 2010).

1.2 Problem Background

Formerly, the research of brain-computer interfaces (BCIs) has rapidly evolve significantly as well as research in the field of Emotion Recognition and Classification is also emerge parallel with its development. Making robots acts socially by giving it an ability to read other's emotion and act accordingly would make the interaction more human-like and increase the effectiveness of Human Robots Interactive (Schaaff & Schultz, 2009a).

In earlier times, such efforts and attempts have been prepared and focused to recognize the emotion with different technique such as recognition from facial expression and speech signal analysis that achieved varying degree of accuracy. The recognition of the emotion from facial expression achieved the maximum average of accuracy from 70% to 80% under controlled environment can be conclude into something possible (Bos, 2006). It is by reason of the emotions that can be purposefully expressed and can be hidden by the subjects.

Sometimes the emotions are not totally displayed or revealed by the human or there are humans that incapable to describing their emotion due to some dysfunction of emotion awareness. In psychology, explicit differentiation has been made among the physiological arousal and behavioural expression (Bos, 2006). Obscurity of a difference between emotion classifications led to obstacles in classifying the emotions where each person is different in expressing their emotional state. Thus, it is not a simple task to determine the emotions.

The second aspects of emotion which is expressive behaviour that involved facial expression, body language, posture, and voice which can be easily adapted and its interpretation is very subjective. These cause lead to the interest of physiological arousal aspects involved brain activity, body temperature, Galvanic skin response and heart rate (Bos, 2006; Picard & Klein, 2002). A study assumes that the change of emotion influence the reaction in the nervous system that change the state of brain. Thus, several studies on Emotion Recognition and Classification have been carried out using the electroencephalogram signals (EEG) (Bos, 2006; Murugappan et al., 2010; Singh et al., 2013; Yuen et al., 2011). The different aspects of methods and techniques used in the study influence the variation of results. The diversities involved the emotion selection, experiment environment, data preprocessing techniques, feature selection and classification or recognition techniques. All the aforementioned factors lead to the difficulty in comparing and choosing the best method for the classification. Hence, there are opportunities for the development of suitable and better classifier for specific variables and objectives.

This study will focus on implementing the features extraction method in identifying a set of suitable features in order to extract the valuable information of electroencephalogram signals (EEG) and implement the applicable classifier that can be used to identify and classify different types of emotions. Wavelet Transform Analysis and Machine Learning such as Support Vector Machine (SVM) algorithm and Naïve Bayes (NB) algorithm are the promising solution to this type of problem as addresses in the previous study. Wavelet decomposition is a momentary features that are precisely captured and localized in both time-frequency domain as well as reduces the computational load and achieves best performance with finite precision (Subasi & Erçelebi, 2005). Support Vector Machine (SVM) and Naïve Bayes (NB) (NB) are chosen because it possesses a few advantages over other classification techniques. Those algorithms have significant benefits in handling multiple learning tasks with multiple variables. Therefore, Wavelet Transform and aforementioned classifiers will be applied in this study to solve the accuracy issue.

1.3 Motivation

Human have various kind of emotions such as happy, angry, sad, fear, surprise and so on. There are questions that have been focus for years and still haven't found a certain conclusion related to classification accuracy and internal relations in such emotions that require on-going studies to fulfil the concern.

Emotion Recognition believes that human emotional states can be evaluated by analysing human related data. Starting from top of human body which is brain that produces psychological signals, face that forms facial expressions, mouth that generates speech signals, body that delivers body languages and physiological signals are assumed to achieve accurate classification outcomes (Zimmermann, Guttormsen, Danuser, & Gomez, 2003). The characteristics of physiological signals are firstly abstracted by one of the emotion research group from MIT that useful for further studying in emotion recognition and classification. It has been proven that physiological signals is feasible to recognize emotions (Wagner, Kim, & André, 2005).

Electroencephalogram signals (EEG) is bioelectrical signal from the electrical activity in the cortex or surface of the scalp, which is due to the physiological activity of the brain and features of electroencephalogram signals (EEG) differ widely in diverse mental health states, emotional experiences and physiological status. Moreover, the electroencephalogram signals (EEG) always reflects the true emotional state of a person and might not be disposed to fraud when compared to speech and facial expressions (Schaaff & Schultz, 2009a). The implementation system of electroencephalogram signals (EEG) generally contains basic procedures such as signal acquisition and preprocessing, features extraction, modelling and classifying. Electroencephalogram signals (EEG) has wide applications and good effects in various fields.

The importance of emotion in human-computer interaction was realized since a few years backward. Subsequently, the research in affective computing that related to emotions is emerging and a concern as many people have difficulties with the logical and rational way in which computers react both displaying emotional actions plus empathic behaviour (Schaaff & Schultz, 2009b).

1.4 Problem Statement

Electroencephalogram signals (EEG) usually contains enormous amounts of data with countless categories. The signals turn out to be more burdensome during evaluating task if the data is captured over a long time period. The robust approaches are necessary to acquire the hidden significant and valuable information produced by the activity in human brain that buried within the signals. Thus, proper and applicable methods are developed to analyse and classify the data. Even though there are lots of previous researches and works associated to the aforementioned task, both features extraction and classification have not been well developed in achieving greater accuracy. The evaluation of Electroencephalogram signals (EEG) generally piloted by experienced Electroencephalographers who is in charge of capturing the signal records (Subasi & Erçelebi, 2005).

The proposal of an operative and efficient classification system is likely to be complex with the complexity of the signals and its countless information and the existence of diverse subjects and target. Currently, there are numbers of analysis methods that have been proposed and suggested with respect to extract the relevant and valuable information from the raw signals as well as classifying distinctive classes of data. From the collected works in literature, the observation concluded that some of the described methods had an inadequate achievement rate of accuracy or classification performances. Several studies are using incompatible feature extraction that will affect the achievement. Moreover, the complexity of algorithm causes a time consuming systems in performing the required calculation and computation task then finally turn out to be impractical for applications. In addition, the numbers of sample data used in experiments and the data formatting as well as representation also notably impact the accuracy of the classification systems. Generally, there are masses of issues influence the classification performance other than the above-mentioned issues. In some of the circumstances, the reported techniques which executed in their experiment are improper due to the lack of understanding of practices in selecting and extracting the valuable parameters. There are certainly limited available benchmark databases of electroencephalogram signals (EEG) with labelled emotions. Though, expansion and improvement of procedures is needed to improve the accuracy.

To investigate and explore the issues, in this dissertation, approaches were proposed for the emotion classification of Electroencephalogram signals (EEG) which are able to provide high accuracy. The study of this dissertation addresses and investigates the following problems: the best suitable features and affective methods for feature extraction of electroencephalogram signals (EEG). Specifically, this study as well investigates and provides an evaluation of effective methods for classifying the emotions using selected classification technique.

The main questions in this research are:

i. How to implement the feature extraction method to extract the best features of electroencephalogram signals (EEG)?
ii. What are the best features to extract from the electroencephalogram signals (EEG) which can be mapped to specific emotional state?

iii. How to implement the classification approach to classify the emotion?
iv. How to find the efficiency of the classifier in classifying the emotion?
v. How accurately the electroencephalogram signals (EEG) can be classified?

1.5 Research Aim

The aim of this project is to implement the features extraction method in identifying a set of best features that can be used to extract all the valuable information from the electroencephalogram signals (EEG) and implement the selected classifier that can be used to effectively classify the emotion as well as its accuracy in classifying the electroencephalogram signals (EEG) to specific emotional state.

1.6 Objectives

In order to achieve the aim of the project, the research follows these three objectives:

i. To propose new wavelet based features that can be used to classify emotion from electroencephalogram signals (EEG).
ii. To implement suitable classification model to classify emotion from electroencephalogram signals (EEG).
iii. To determine the appropriate bands and channels that associated with the emotion from electroencephalogram signals (EEG).

1.7 Scope

This research was conducted within the scope described below:

i. The dataset used for the experiments is a standard dataset consists of the electroencephalogram signals (EEG) data acquired from DEAP Database.
ii. The dataset used for the experiments did not include ambiguous samples of the electroencephalogram signals (EEG).
iii. The analysis is conducted on this dataset by using the selected analysis and classification algorithm to classify emotions.
iv. This study will only focus on classifying positive/negative arousal and valence emotions.
v. The performance of the classifiers is evaluated based on classification accuracy and F-Score of the model.

1.8 Dissertation Organization

This dissertation is organized as follows:

i. Chapter 1 introduces the introduction to emotion and electroencephalogram signals (EEG) domain, background of the problem, motivation behind the research, problem statement, research aim, objectives and research scopes.
ii. Chapter 2 describes the related literatures of the emotions, electroencephalogram signals (EEG), features extraction, and classification technique as well as previous work related to classifying emotion based on electroencephalogram signals (EEG).
iii. Chapter 3 illustrates the methodologies of this research such as data preparation, data preprocessing, data model development and evaluation of the model.

iv. Chapter 4 reports the result and discussion from the experiments that are conducted with the purpose of achieving the objective of the research. Wavelet Transform and classifiers model are further discussed to show which features and classifier had better performance results.

v. Chapter 5 concludes the conclusion and contribution of the study that have been conducted with the purpose of achieving the objective of the research. The discussion then completes with recommendations for future works.

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