EEG-BASED EMOTION CLASSIFICATION BY USING CONVOLUTIONAL NEURAL NETWORK (CNN)

TONG SIAU KHEE

UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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TONG SIAU KHEE

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To dear family and friends that give guidance and support to me

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ABSTRACT

Emotion is an essential component in social interaction and communication which act as a guideline in decision making or planning. It is believed that emotion can help to bridge the gaps between human and computer. However, emotion detection through facial expression or speech detection that existing nowadays is not accurate enough because it can be faked. Therefore, a EEG-based emotion classification system is proposed to analyse the "inner" emotion through the brain activity. Convolutional neural network (CNN) technique is applied to perform feature extraction and classification for the labelled EEG signal. This method aims to replace the expensive traditional hand-crafted feature extraction method. Based on the spatial temporal characteristics of EEG signal, two CNN architectures are built by referring to the previous researches. It was tested with EEG dataset that acquired from 32 subjects by using pictures from IAPS database as stimuli and verified by using SEED dataset. The system able to achieve an average accuracy of 75% in classifying 3 emotions (positive, neutral, negative) from SEED dataset. However, it only able to achieve average accuracy of 30% for 4 class of emotions and 59% for 2 class of emotions from self-conducted dataset due to the insufficient of training data.

ABSTRAK

Emosi merupakan satu perkara yang penting dalam interaksi sosial dan komunikasi yang bertindak sebagai garis panduan dalam membuat keputusan atau perancangan. Adalah dipercayai bahawa emosi dapat membantu merapatkan manusia dengan komputer. Walau bagaimanapun, pengesanan emosi melalui ekspresi wajah atau pengesanan ucapan yang sedia ada pada masa kini tidak cukup tepat kerana ia boleh dipalsukan. Oleh itu, satu sistem klasifikasi emosi berdasarkan EEG telah dicadangkan untuk menganalisis emosi dalaman manusia melalui aktiviti otak. Teknik konvolusi rangkaian neural (CNN) telah digunakan untuk melaksanakan pengekstrakan ciri dan klasifikasi bagi isyarat EEG yang dilabel. Kaedah ini bertujuan untuk menggantikan kaedah pengekstrakan ciri tradisional yang rumit. Berdasarkan ciri-ciri temporal spatial isyarat EEG, dua seni bina CNN telah dibina dengan merujuk kepada kajian sebelum. Kaedah CNN ini telah diuji dengan EEG data yang diperolehi daripada 32 sukarelawan dengan menggunakan gambar daripada pangkalan data IAPS sebagai rangsangan dan disahkan dengan menggunakan SEED set data. Sistem ini dapat mencapai ketepatan purata 75% dalam mengklasifikasikan 3 emosi (positif, neutral, negatif) daripada SEED set data. Walau bagaimanapun, ia hanya mampu untuk mencapai ketepatan purata 30% untuk 4 kelas emosi dan 59% untuk 2 kelas emosi daripada dataset yang diperolehi daripada eksperimen yang dijalankan. Hal ini disebabkan kekurangan set data untuk pembelanjaran CNN.

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LIST OF ABRREVIATIONS AND ACRONYMS

CNN Convolutional neural network ECG Electrocardiogram _ EEG Electroencephalograms _ fMRI Functional magnetic resonance imaging -HVHA -High valence high arousal HVLA High valence low arousal -IAPS International Affective Picture System -KNN K-nearest neighbors -LVHA Low valence high arousal _ LVLA Low valence low arousal _ MEG Magnetoencephalography -PET Positron Emission Tomography _ PSD Power spectrum density -SEED SJTU emotion EEG dataset _ SNR Signal to noise ratio -SVM Support vector machine -TMSi Twente Medical Systems International Porti system -TTL Transistor-transistor logic pulse -UTeM Universiti Teknikal Malaysia Melaka -

CHAPTER I

INTRODUCTION

This chapter portrays the overview of this project. It starts with a general introduction to this project and follows by the problem statement, objective and scope of work. The structures of this dissertation are listed at the last section of this chapter.

1.1 **Project Overview**

Emotion is a reaction to stimuli that last for seconds or minutes, it also defined as the projection of a feeling [1]. As the technology of emotion is advancing, the demands of emotion recognition have been increasing in this few years. It was believed that emotion recognition system can help to bridge the gap between human and machine interaction. Besides, a machine with emotion recognition will become more intuitive and vivid. "Pepper", a humanoid robot invented by Aldebaran Robotics and Softbank is a good example to show the significant to deploy emotion classification in a robot [2].

There are a lot of successful research have been done to decode human emotion for example by using text, speech and facial expression. One of the new direction for emotion classification research is done by using the Electroencephalograms (EEG) signal due to the increasing popularity of the brain-computer interface that allows interaction between human and computer through the brain signal. To achieved this classification method, various of psychophysiology studies have been carried out to investigate the relationship between emotions and EEG signal. It is reported that EEG signal contains high temporal resolution which can react immediately to emotional stimuli and it is more reliable compared to the external appearance clues that can be fake [3]. Machine learning is a field of study that provides computer with the ability to learn without being explicitly programmed. Conventionally, researchers are working on feature extraction to extract the important feature of the EEG signal using methods such as power spectrum density (PSD), wavelet analysis and correlation analysis. Next, the resulting features are classified using different classifiers such as support vector machine(SVM), K-nearest neighbors (KNN) and regression method. However, EEG signals contain low signal to noise ratio which lead to difficulty in analysing process by using the conventional method. Hence, deep learning technique that allows automated feature extraction is introduced in recent year to eliminate the complex and expensive hand-crafted feature process.

Based on research, deep learning works well in different classification problem especially in image and speech domain [4][5]. It arises as one of the powerful neural network techniques which having at least an additional convolutional layer in the neural network architecture with the weight sharing scheme that helps to reduce the overfitting issue. Recently, deep learning technique was successfully applied in physiological signal and get a good result compared to conventional shallow models.

Therefore, in the project, deep learning technique is implemented to classify EEG signal from different subjects into different emotions. First, an experiment is designed and carried out to collect the EEG signal with different emotion states. Next, the pre-processed signal is feed into the designed CNN architecture to perform feature extraction and classification. By analysing the weight distribution learned from the Convolutional Neural Network, different setup of frequency bands and channels have been done and the performance for each set up are compared. Besides, the constructed CNN architecture is tested with an open source EEG dataset (SEED) to verified its performance.

1.2 Objective

The objectives of this project are listed as below:

i. To design and develop an experiment to acquire EEG signal with different emotions

- ii. To validate the developed classifier by using open sources database
- iii. To design and develop an emotion classification system based on EEG signal by using Convolutional Neural Network (CNN)

1.3 Problem Statements

Emotion detection through speech, audio and facial expression elements are not persuasive enough because human can fake their own expression and vocal intonation anytime. Other neuroimaging methods such as functional magnetic resonance imaging (fMRI) are not suitable for practical emotion classification system due to the cost and immobility. Therefore, EEG signal with high temporal resolution and able to change according to emotion state becoming interesting due to higher accuracy compare to the external appearance that can be altered [6].

EEG is a non-invasive neuroimaging method to record the oscillation of brain electric potentials resulting from ionic current flow between brain neurons. It is ubiquitous, non-invasive and having excellent temporal resolution compare to other neuroimaging method. However, working with EEG signal poses some challenges, the spatial resolution for EEG signal is low and it contains low signal to noise ratio (SNR) which lead to complexity in traditional hand feature extraction. Therefore, a deep learning technique, Convolutional Neural Network (CNN) is introduced as a classification method in this project due to it can generalise well and able to extract important feature automatically through the operation inside.

The available benchmark databases of EEG signal labelled with emotions is less. However, there are labelled databases for emotion induction, hence, an experiment is carried out to collect the EEG signal with emotion by using the standardised picture databases, IAPS.

1.4 Scope of Work

This project focuses on emotion classification by using EEG signal as input and Convolutional Neural Network as the classifier. The classifier able to classify two to four emotions in offline mode. The pre-process of EEG signal is done by using MATLAB program whereas the training and classification algorithms are developed by using Tensorflow with python environment.

This system is trained with EEG data that get from self-conducted experiment and open source EEG library (SEED). For self-conducted experiments, it is based on the bipolar model of emotion, total four emotions are included (Happy, Sad, Afraid, Relax). The stimuli that used to evoke the emotion during the data collection experiment is selected from a standardized database, IAPS and signals are collected from 32 voluntary students in Universiti Teknikal Malaysia Melaka (UTeM). TMSi is used as the EEG recording devices and the total channels included are 22 which based on the International 10-20 system. For online data set, the emotion model is based on discrete emotion model rated by subjects through survey. Three emotions (positive, negative and neutral) are included in this study and the stimuli to evoke the emotion are film clips that related to different emotion state. There are 15 subjects involved in this dataset collection, ESI NeuroScan system is used as the recording device and total of 62 channels based on International 10-20 system are included in this study. The summary of the data used is shown in Table 1.1.

Table 1.1: Summary of data used in this project

Source of data	Self-conducted experiments	From online dataset (SEEDdata)
Emotion	Based on bi-polar model	Based on discrete emotion model
No. of classified emotion	Four emotions	Three emotions
Stimuli	Pictures (IAPS)	Video (Online rating)

1.5 Structure of Thesis

This thesis consists of five chapters. Chapter I is the introduction of this research. This chapter gives an overview of the project by explaining the objective, problem statement and scope of the project. Chapter II give the brief overview of related theory and research on emotion classification using EEG signal as well as the use of Convolutional Neural Network for EEG signals classification. Next, the details of materials and methods that used to implement this system are presented in Chapter III. The methods included experiment design process and the details architecture for CNN. Chapter IV summarised the results from different findings. Lastly, Chapter V draws the conclusion of this research. Suggestions have been made for future implementation.

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CHAPTER II

LITERATURE REVIEW

This chapter covers the related theory and related work for this project. Firstly, the theory of emotion is discussed and different emotion models are reviewed. For classifying emotion from EEG signal, information about the relationship between brain activity and emotions is needed. Therefore, part two of this chapter reviews about the EEG signal and how EEG signal related to emotion. Part three of this chapter discusses the working principle of machine learning and Convolutional Neural Network (CNN). Related research on EEG signal by using CNN is compared and analysed.

2.1 Emotion and Emotion Model

Emotion can be defined as the feeling that involves thoughts, physiological changes and expression [7]. Different theories state different sequences for the thoughts and physiological change. From James-Lange theory, emotion is the experience of some change in the human body, it occurs due to physiological reaction to certain event, for example, a human can be stated he is feeling afraid due to his body was trembling after he saw a cockroach. Later, Cannon-Bard theory of emotion argues that human will experience the emotion and physiological reactions simultaneously [8]. No matter how the sequences are, scientists agreed that the origin of emotion is from human brain [9].

Generally, emotion can be divided into discrete model and dimensional model. Discrete model of emotion is based on one of core emotions for example happy, afraid, sad or combinations of two core emotions. There are some theories about the discrete model. Ekman stated that emotion can be classified into six different classes which include anger, fear, disgust, happiness, sadness and surprise and all these emotions are associated with facial expression. Later, he strengthens his previous writing [10] by adding amusement, anger, contempt, contentment, disgust, embarrassment, excitement, fear, guilt, pride in achievement, relied, sadness/distress, satisfaction, sensory pleasure and shame [11]. In 1980, a psychologist name Robert Plutchik proposed eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. He developed the wheel of emotion (Figure 2.1) to show how a new emotion state creates by combining multiple emotion states.



Figure 2.1: Wheel of emotions [12]

However, it is hard to differentiate emotion in discrete form because the thought of emotion for every person is different over different culture and age. Therefore, a multidimensional model is proposed to prevent overlapping of emotion. The multi-model interprets emotions through levels of valence and arousal and it is first advocated by Russell [13]. Figure 2.2 shows the bipolar model with arousal (y-axis) and valence (xaxis) dimensions. Valence indicates the quality of emotion, it is range from negative to positive whereas arousal shows the arousal of emotion which range from calm to excited.



Figure 2.2: Bi-polar model of emotion [14]

Most of the researches applied this model to differentiate emotion due to its simplicity and universality. Besides that, dimensional model is preferable compared to discrete model because it is easier to compare the findings between two different studies with valence and arousal dimension. Moreover, it can be used to locate discrete emotion based on the person point of view [11].

2.2 Electroencephalogram (EEG)

EEG stands for Electroencephalogram. It is a test uses to monitor the electrical activity of the brain by comparing to the voltage different between two location on cerebrum of a human[15]. EEG test is normally represented as the signal over time and it is done by placing the electrode on the scalp of a human, the electrode position is usually based on the standardised International 10-20 system. The history of EEG begins with Richard Caton, the first physician that discovered the relationship between the brain and electric current in 1875 from exposed brains of rabbits and monkeys using mirror galvanometer[16]. In 1924, a physiologist name Hans Berger done the very first human EEG measurement with a 17-years old boy and was exposed to the frontoparietal of cortex. Besides, he also invented the word "electroencephalogram" and proposed his first report related to human EEG in 1929. 10 Hz alpha wave names as "Berger wave" and he also