DISCRETE WAVELET PACKET TRANSFORM FOR ELECTROENCEPHALOGRAM BASED VALENCE-AROUSAL EMOTION RECOGNITION

OYENUGA WASIU OLAKUNLE

MASTER OF SCIENCE
UNIVERSITI UTARA MALAYSIA
2015

Permission to Use

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to:

Dean of Awang Had Salleh Graduate School of Arts and Sciences
UUM College of Arts and Sciences
Universiti Utara Malaysia
06010 UUM Sintok

Abstrak

Pengecaman emosi berasaskan elektroensefalogram (EEG) telah mendapat perhatian yang tinggi.Hal ini disebabkan ianya adalah suatu kaedah tak invasif untuk mendapatkan isyarat daripada otak dan ianya boleh menunjukkan keadaan emosi secara terus. Walau bagaimanapun, isu-isu yang mencabar berkaitan pengecaman keadaan emosi berasaskan EEG ini adalah ianya memerlukan kaedah dan algoritma yang direka bentuk dengan baik dan proses untuk mendapatkan ciri-ciri yang diperlukan daripada isyarat EEG yang kompleks, tidak menentu dan berbilang saluran demi memperoleh prestasi pengelasan yang optimum. Tujuan kajian ini adalah untuk membongkar kaedah pengeluaran ciri dan kombinasi beberapa saluran elektrod yang melaksanakan pengecaman emosi valens-kebangkitan yang berasaskan EEG yang optimum. Berdasarkan hal ini, eksperimen telah dijalankan terhadap dua pengecaman emosi untuk mengelaskan keadaan emosi manusia kepada valens tinggi/rendah atau kebangkitan tinggi/rendah. Eksperimen yang pertama bertujuan untuk menilai prestasi Pengubahan Diskret Riak Paket (DWPT) sebagai satu kaedah pengeluaran ciri. Eksperimen kedua adalah bertujuan untuk mengenalpasti kombinasi saluran-saluran elektrod yang mengecam emosi dengan optimum berdasarkan model valens-kebangkitan dalam pengecaman emosi EEG. Dalam menilai hasil kajian ini, satu penanda aras digunakan untuk melaksanakan pengelasan emosi. Dalam eksperimen pertama, ciri-ciri entropi bagi jalur teta, alfa, beta dan gama dikeluarkan melalui 10 saluran EEG iaitu Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, dan O2 menggunakan DWPT dengan Mesin Jejarian Asas Fungsi-Sokongan Vektor (RBF-SVM) digunakan sebagai pengelas. Dalam eksperimen kedua, eksperimen pengelasan diulang dengan menggunakan 4 saluran frontal EEG Fp1, Fp2, F3 dan F4. Keputusan eksperimen pertama menunjukkan ciri-ciri entropi yang dikeluarkan dengan menggunakan DWPT adalah lebih baik daripada ciri-ciri kuasa jalur. Manakala keputusan eksperimen pengelasan kedua menunjukkan kombinasi 4 saluran frontal lebih signifikan daripada kombinasi 10 saluran.

Kata kunci: Pengubahan Diskret Riak Paket, Elektroensefalogram, Pengecaman emosi, Entropi, Fungsi Jejarian Asas, Mesin vektor sokongan.

Abstract

Electroencephalogram (EEG) based emotion recognition has received considerable attention as it is a non-invasive method of acquiring physiological signals from the brain and it could directly reflect emotional states. However, the challenging issues regarding EEG-based emotional state recognition is that it requires well-designed methods and algorithms to extract necessary features from the complex, chaotic, and multichannel EEG signal in order to achieve optimum classification performance. The aim of this study is to discover the feature extraction method and the combination of electrode channels that optimally implements EEG-based valence-arousal emotion recognition. Based on this, two emotion recognition experiments were performed to classify human emotional states into high/low valence or high/low arousal. The first experiment was aimed to evaluate the performance of Discrete Wavelet Packet Transform (DWPT) as a feature extraction method. The second experiment was aimed at identifying the combination of electrode channels that optimally recognize emotions based on the valence-arousal model in EEG emotion recognition. In order to evaluate the results of this study, a benchmark EEG dataset was used to implement the emotion classification. In the first experiment, the entropy features of the theta, alpha, beta, and gamma bands through the 10 EEG channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 were extracted using DWPT and Radial Basis Function-Support Vector Machine (RBF-SVM) was used as the classifier. In the second experiment, the classification experiments were repeated using the 4 EEG frontal channels Fp1, Fp2, F3, and F4. The result of the first experiment showed that entropy features extracted using DWPT are better than bandpower features. While the result of the second classification experiment shows that the combination of the 4 frontal channels is more significant than the combination of the 10 channels.

Keywords: Discrete wavelet packet transform, Electroencephalogram, Emotion recognition, Entropy, Radial basis function, Support vector machine.

Acknowledgement

All praise is due to Allah, who by His grace I completed this task. May His peace and blessing be upon His prophet, Muhammad (S.A.W.).

Special thanks to my Mother and Father for their love and guidance. I also thank my dear wife for her love, passion and understanding throughout my studies. I wish to also thank my brothers and sisters for caring about me during times of ease and hardship. I will like to show gratitude to my supervisor Dr. Farzana Kabir Ahmad for her guidance and patience during this research work. I will also like to extend my gratitude to Associate Professor Fadzilah Siraj, Dr. Nooraini Yusoff, Dr. Husniza Husni, and Dr. Azizi Bin Ab Aziz, I have gained a lot from them all that have contributed to the success of this work.

Thank you all may Allah help you too.

Table of Contents

List of Tables

List of Figures

List of Abbreviations

ANN-	Artificial Neural Networks
ANS-	Autonomic Nervous System
CNS-	Central Nervous System
DEAP-	A Database for Emotion Analysis Using Physiological Signals
DWT-	Discrete Wavelet Transform
DWPT-	Discrete Wavelet Packet Transform
EEG -	Electroencephalogram
EOG -	Electrooculogram
ERP-	Event Related Potentials
FD-	Fractal Dimension
fNIRS -	Functional Near-Infrared Spectroscopy
GA-	Genetic Algorithm
IADS-	International Affective Digitized Sounds
IAPS-	International Affective Picture System
KNN-	K-Nearest Neighbour
LDA-	Linear Discriminant Analysis
NB -	Naïve Bayes
PCA-	Principal Component Analysis
PSD-	Power Spectral Density
RPA-	Recurrence Plot Analysis
RBF-	Radial Basis Function-Support Vector Machine
SAM-	Self-Assessment Manikins
SVM-	Support Vector Machine

CHAPTER ONE
INTRODUCTION

1.1 Introduction

Human beings express various emotions during daily activities and interactions with other people. In human daily interactions, these emotions are recognized through facial expression, voice, or body gesture. The task of recognizing emotions is simple for human, however computers capability of recognizing human emotions is still diminished (Amaral, Ferreira, Aquino, and Castro (2013).

In affective computing, facial expressions, body gestures, and vocal intonation have been used to recognize human emotions (Fu, Yang, and Hou, 2011). However, due to the fact that human can control the facial expressions, body gestures, and vocal intonation voluntarily, various studies have used physiological bio-signals from the peripherals of the human body to recognize emotions (Kim, Bang, and Kim, 2004; Kim and André, 2006; Kim and André, 2008; Picard, Vyzas, and Healey, 2001). The electrical signals from the brain itself acquired by Electroencephalograms (EEG) are recently used to recognize human emotions (Jatupaiboon, Pan-ngum, and Israsena, 2013; Lin, Wang, Jung, Wu, Jeng, Duann and Chen, 2010; Wang, Nie, and Lu, 2011).

The non-linearity, non-stationary, and chaotic properties of the EEG signals have created great problems that lead to thorough signal processing and analysis (Sanei and Chambers, 2008). In other words, to achieve optimal results, there is a need to systematically choose the methods and techniques that will be applied when implementing emotion recognition using EEG signals. This problem calls for more research in this field in order to attain better and more accurate results in EEG signal processing and analysis.

1.2 Background of the Study

This section presents the bases of emotion recognition and how EEG can be used for acquiring the neural activities of the brain in order to recognize emotions.

1.2.1 Emotion Recognition

According to Torres, Orozco, and Alvarez (2013), emotion is "a psycho-physiological process that affects the behaviour of an individual with respect to a particular situation, and plays an important role in human communication. Emotion has also been defined as "a psychological state or process that functions in the management of maintaining the balance of information processes in the brain and the relevant goals" (Stickel, Ebner, Steinbach-Nordmann, Searle, and Holzinger, 2009).

Conventional approaches such as studying facial expressions, body gestures, and vocal intonations have been used in affective computing for recognizing human emotions (Lin et al., 2010). The results from these approaches were not reliable and not satisfactory, for the fact that human could control their facial expression, body gestures, or vocal intonation voluntarily (Liu, Sourina, and Nguyen, 2011; Singh et al., 2012). For this reason, researches have been conducted using some physiological responses in recognizing human emotions. This approach uses various magnetic or electronic devices to assess some bio-signals from the human body. The results from the use of physiological responses provide more detailed information in recognizing different human emotions states (Lin et al., 2010).

The earlier methods of recording these bio-signals were via the Autonomic Nervous System (ANS) such as respiration rate, pupil dilation, blood pressure, heart rate, papillary dilation or contraction, galvanic skin resistance, pulse rate (Bos, 2007). Recently researchers were able to gain more insight in recognizing different human emotion states via the Central Nervous System (CNS), using signals from the brain activity that were recorded from the scalp with the aid of an electronic device called EEG (Singh et al., 2012). Signals captured through EEG have been proved to be more effective in providing more information on mental activities and emotional states. Therefore compared to the bio-signals from the ANS, emotions can better be recognized using EEG (Chanel, Kronegg, Grandjean, and Pun, 2006).

1.2.2 Brain Activities in Emotional States

The brain cells called neurons are responsible for generating signals or electrical pulses in the brain. Neurons generate these electrical pulses for the purpose of communicating with other neurons. These electric pulses are called action potentials or spikes. An action potential occur when there is fast opening and closing of sodium and potassium ion channels on the neuron membrane causing fast inflow of sodium ions and slower outflow of potassium ions. As a result, a rise in voltage will occur inside the cell and when this voltage increase reaches a certain threshold, a spike will occur (Dayan and Abbott, 2000).

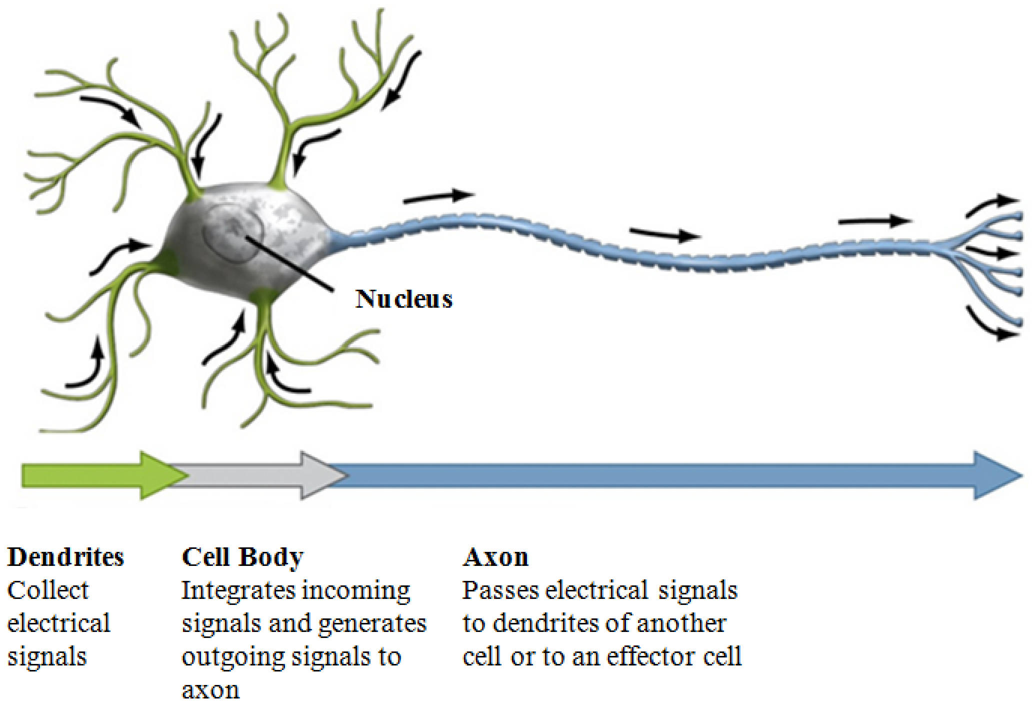


Figure 1.1. Information Flow within a Neuron (Source: www.uic.edu (Edited))

Neurons communicate by firing sequences of spikes. These spikes travel from the axon of a neuron to the dendrite of another neighbouring neuron. These processes together represent the brain electrical activity (Dayan and Abbott, 2000). This electrical activity can be acquired with EEG placed on the scalp and it represents the field potentials resulting from the combined activity of many neurons (Bos, 2007).

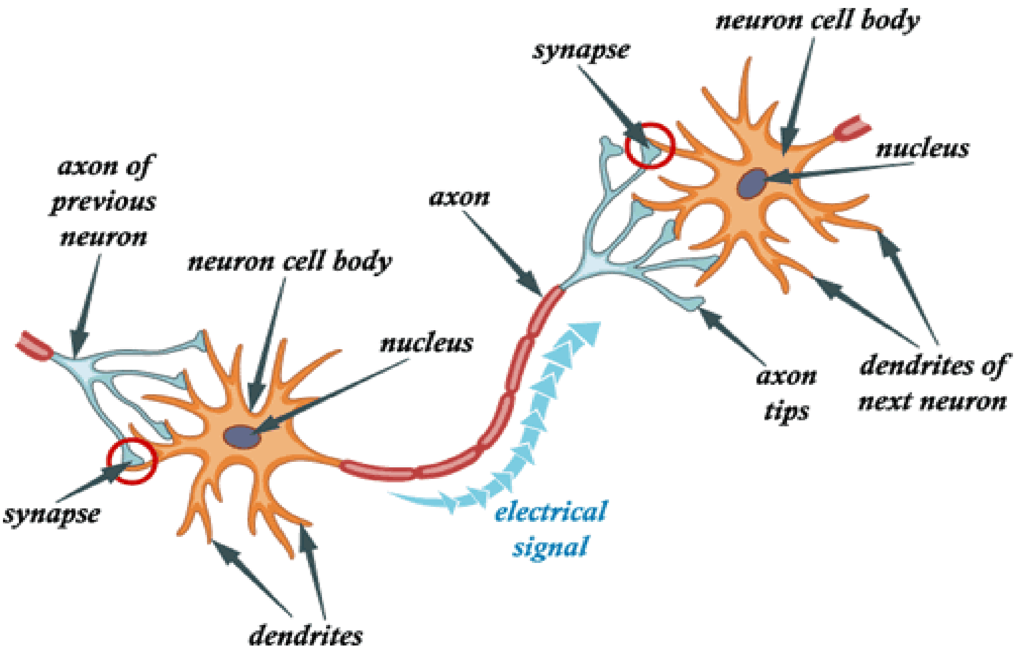


Figure 1.2. Information Flow between Neurons

The human brain can be divided into three main parts, namely, cerebellum, brain stem, and cerebrum, as illustrated in Figure 1.3. Each of these parts participate in different states of emotions,

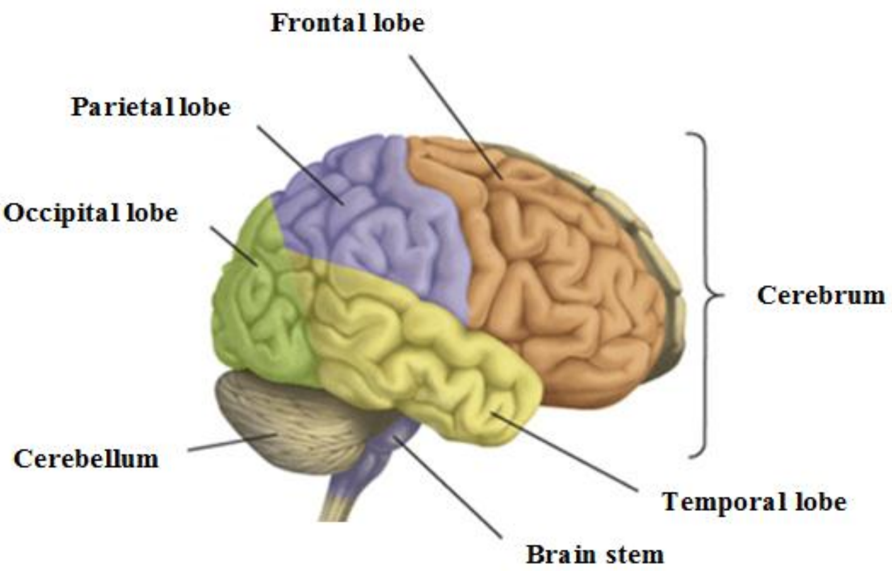


Figure 1.3. Parts of the Human Brain

Cerebrum is the largest and most prominent part of the brain and it is split longitudinally into two; the right and left hemispheres as illustrated in Figure 1.4. Each hemisphere is further divided into the frontal, parietal, temporal, and occipital lobes.

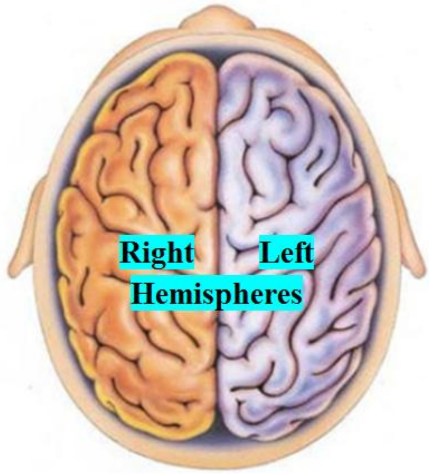


Figure 1.4. Right and Left Hemispheres

The layer on the outer surface of the cerebrum is called the cerebral cortex while the inner part comprises of several sub-cortical structures, Figure 1.5. These sub-cortical structures include the hippocampus, amygdale, thalamus, basal ganglia, and olfactory bulb.

The frontal, temporal, and parietal lobes of the cerebral cortex, and the basal ganglia, thalamus, amygdale and hippocampus of the sub-cortical regions are the parts of the brain responsible for emotion processing (Singh et al., 2012). The cerebral cortex is densely packed with neurons therefore much of the neural activities of the brain take place within this layer. Due to the fact that this layer is close to the skull, the brain activities can be read with EEG placed of the scalp. On the other hand, the activities in the sub-cortical areas which lies in the inner region of the brain cannot be read using EEG placed of the scalp (Bos, 2007).

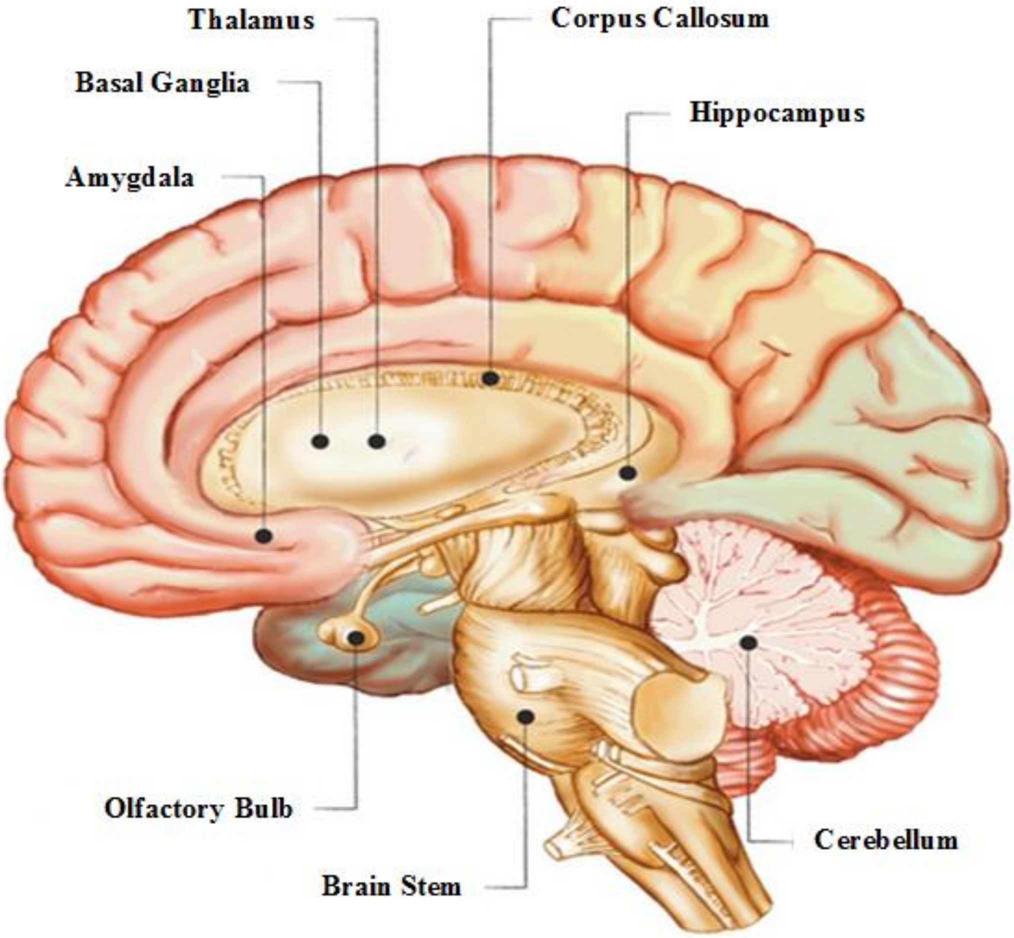


Figure 1.5. The Sub-Cortical Structures (Source: tantrum911.com (Edited))

Research has shown the relationship between the activities in the frontal lobe and emotions**;** a great activity in the left frontal lobe region is associated with motivated and positive reactions, while a great activity in the right frontal lobe region is associated with avoidance and negative affect (Garcia–Molina et al., 2013). For this reason, most researchers acquire EEG signals for emotion recognition from electrodes placed on the frontal lobe of the brain.

1.2.3 Methods of Acquiring Electrical Signals from the Brain

Practically there are two ways of acquiring electrical signals from the brain. One method is by physically implanting one or more electrodes inside the brain, this method is known as the invasive or intracranial method. Another method known as the non-invasive method is when EEG is placed on the scalp (Sanei and Chambers, 2008). Though the invasive method gives more access to neural activity as it allow access to a single neuron or very local field potentials. However, it is avoided due to the fact that it requires surgery and also the results from the non-invasive methods are very encouraging.

To acquire raw EEG data using the the non-invasive method, electrodes are placed on the scape of participants following some standard of EEG electrode montage. One of the standardized sets of electrode location system is the 10-20 system shown in Figure 1.6. The conventional 10-20 system allows 21 electrode positioning. The system was later modified to accommodate more electrodes. Researchers perform experiments that are aimed at achieving some objectives. Number of electrodes used in experiments varies from 1 to 64 electrode channels or more according to the aim of the experiment.

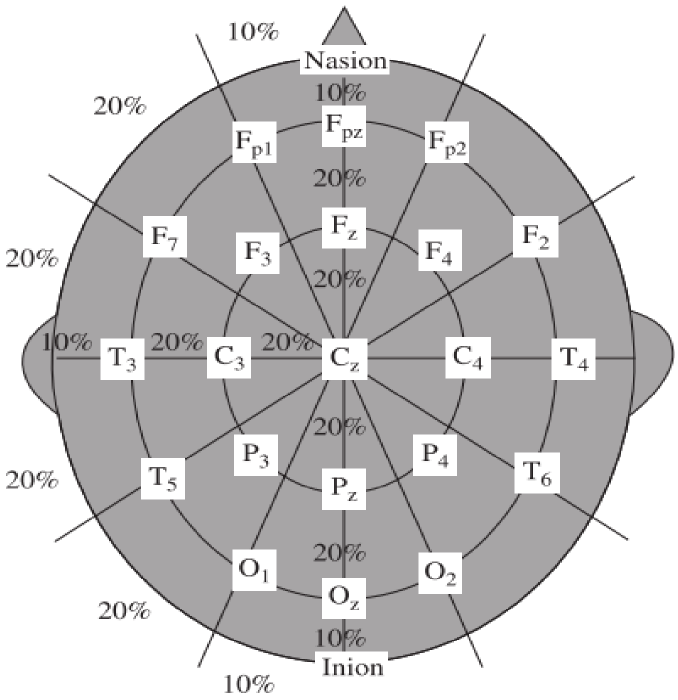


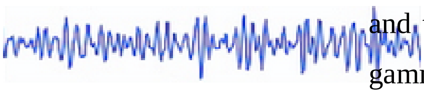
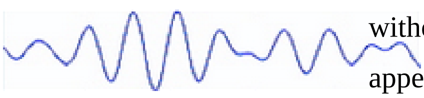
Figure 1.6. The 10–20 Positioning for 21 Electrode Channels (Sanei and Chambers, 2008)

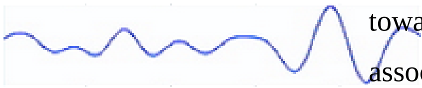
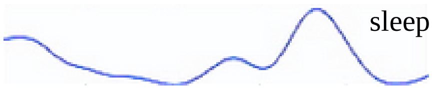
Figure 1.7. EEG Montage

1.2.4 Characteristics of EEG Signals

Electrical waves that occur as a result of neural activities are referred to as the brain waves. These waves are characterised by their frequency and amplitudes. There are five major brain waves which are distinguished by their different frequency ranges. Delta (δ), theta (θ), alpha (α), beta (β), and gamma (γ) are the frequency bands, from low to high frequencies respectively. The amplitudes vary from 10 to 100 micro volts (μV) (Sanei and Chambers, 2008). The delta wave is observed in infants and sleeping adults, the theta wave in children and sleeping adults, the alpha wave is detected in the occipital brain region when there is no attention, and the beta wave appears in the frontal and parietal lobes with low amplitude. A further description of these waves by Sanei and Chambers (2008) is shown in Table 1.1.

Table 1.1: *Description of the Brain Waves*

	Waves	**Frequency Range**	**Description**
1	Gamma	>30Hz (mainly up to 45 Hz) 	They are sometimes called the fast beta wave, and their occurrence is rare. The amplitude of gamma waves is also very low.
2	Beta	13 - 30 Hz 	A beta wave usually occur in awake state of the brain associated with active thinking, focused attention, or when solving concrete problems like mathematical problems. A high-level beta wave may occur in a panic state. The amplitude of the beta waves is normally under 30 μV.
3	Alpha	8 - 13 Hz 	Alpha waves indicate both a relaxed awareness without any attention or concentration and it appears mostly with eyes closed. Alpha waves

			is eliminated or reduced by opening the eyes, by anxiety, by hearing unfamiliar sounds, or by mental concentration or attention. An alpha wave has amplitude of normally less than 50 μV.
4	Theta	4 - 8 Hz 	Theta waves appear as consciousness moves towards drowsiness. Theta waves have been associated with creative inspiration and deep meditation. Theta wave is related to the level of arousal. The changes in the rhythm of theta waves are examined for emotional studies.
5	Delta	0.5 - 4 Hz 	Delta waves are primarily associated with deep sleep and may be present in the waking state.

1.2.5 Emotion Elicitation

Emotion elicitation techniques are aimed at inducing a certain affective response in one or more emotion response systems in a controlled setting via some type of stimulus (Garcia–Molina et al., 2013). To induce a certain emotion state, some elicitation techniques has been used with the aid of various kinds of stimuli such as visual, auditory, or audio-visual (combination of visual and auditory). Visual stimuli were used by Mathieu, Bonnet, Harquel, Gentaz, and Campagne (2013). Auditory stimuli were used by Liu et al. (2011). Audio-visual stimuli were used by Singh et al. (2012).

There are labeled databases of visual stimuli and audio stimuli for emotion induction. International Affective Digitized Sounds (IADS) is an example of labeled audio stimuli database (Bradley and Lang 2007) while International Affective Picture System (IAPS) is an example of labeled visual stimuli database (Lang, Bradley, and Cuthbert, 2005). The IAPS is a database of images with an emotional content and IADS is a database of sound or music pieces with an emotional content.

1.2.6 Modelling Emotional States

There is currently no standardized model of categorizing emotions. Previous studies have shown two perspectives of emotion classification: discrete and dimensional. Theories that support the discrete perspective suggested that there are some emotions that form a core set of basic emotions from which all other emotions (secondary) can be formed. One example is Paul Ekman's (1987) six basic emotion; joy, sadness, anger, disgust, fear, and surprise. On the other hand, theories that support the dimensional perspective propose the concept that emotions can be mapped as per their differing in degree on one or another dimension. A well know example is the Circumplex Model of Affect or the Valence-Arousal model by Russel (1980).

The dimensional perspective is preferable in emotion recognition researches due to numbers of advantages over discrete. Some of these advantages are as follows. With dimensional model, it is possible to represent discrete emotions in the space of the dimensional model coordinate system without using labels by giving the emotion a location as point in this space. The intensity of the emotions can as well be represented in this space (Chanel, 2009; Liu et al., 2011).

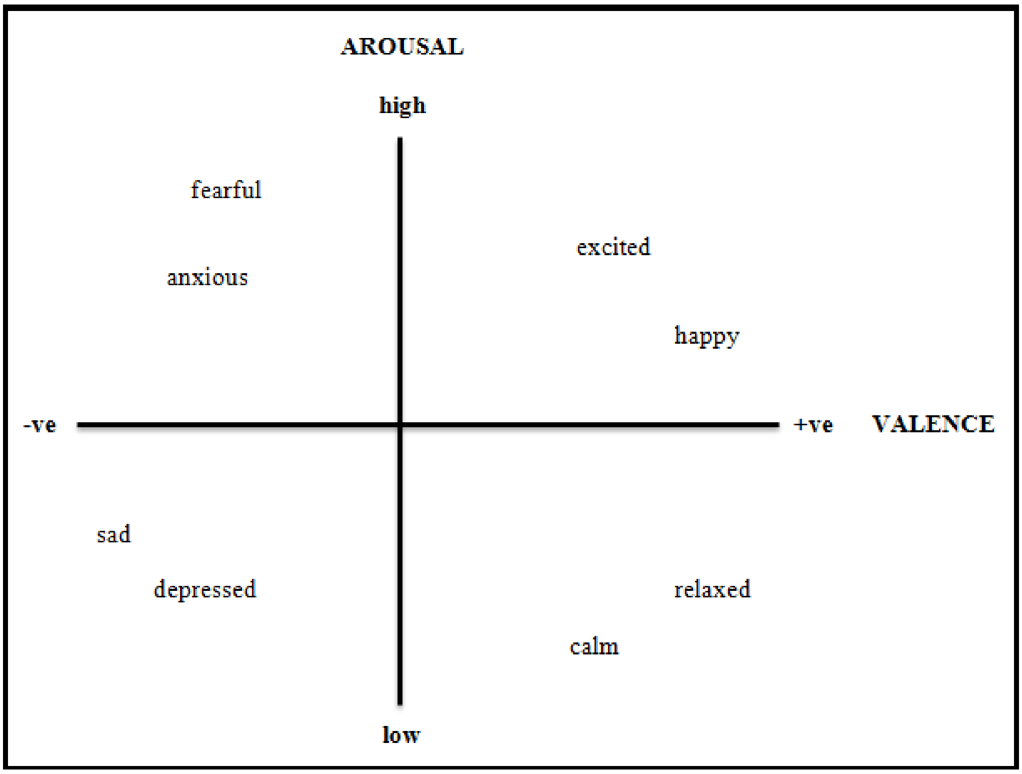


Figure 1.8. An Instance of the Valence-Arousal Model

The Valence-Arousal model is mostly adopted in researches to classify emotions. It is a bipolar model where two orthogonal dimensions, arousal and valence dimensions, are used to model emotions. The valence dimension ranges from highly positive to highly negative, whereas the arousal dimension ranges from excitement or agitation to calmness (Kensinger, 2004; Liu et al., 2011). Discrete emotions can be mapped to the Valence-Arousal coordinate system, for instance sad can be mapped to be negative valence and low arousal.

1.2.7 EEG-Based Emotion Recognition

There are five stages involved in EEG-based emotion recognition experiment. First, raw EEG signals are acquired using the invasive or non-invasive method. The raw EEG data will then be pre-processed by removing noise. The following stage is the feature extraction stage, whereby necessary features are extracted from the EEG signal. The next is the feature selection stage; this is done for dimensionality reduction. Lastly is classification stage. Details of all these stages are discussed in the next chapter.

1.3 Problem Statements

Human emotion recognition is seen has one of the key steps toward advanced human-computer interactions. The advancement in computational algorithms and techniques has recently added to the promising results in emotion recognition researches. In this field of research, the brain signals (electrical potentials) acquired through EEG has proved to be a better method for human emotion recognition (Chanel, Kronegg, Grandjean and Pun, 2006). However, due to the non-linearity, non-stationary, and chaotic nature of the EEG signals, EEG signal processing has been an extensive research area and several signal processing techniques have been tested in order to attain better and more accurate results for EEG signal processing and analysis.

Comparative analyses based on the results from available studies are in some cases not possible. In other words, it is very difficult to conclude on a model due to the fact that various researchers have used different experimental setups and have chosen different set of features to be analyzed in their studies. For example, some studies have performed experimental setup for EEG-based emotion recognition which are different from others (AlZoubi, Calvo and Stevens, 2009; Khalili and Moradi, 2009; Murugappan et al., 2011). In the study carried out by AlZoubi, Calvo and Stevens

(2009), EEG signals were acquired by the 6 bipolar channels F3-F4, C3-C4, Cz-PO, F3-Cz, Fz-C3, and Fz-PO to recognize 10 discrete self-elicited emotions based on Power Spectral Density (PSD) features. Khalili and Moradi (2009) performed own experiment using 54 electrodes to acquire EEG signals to recognize picture elicited emotions on three classes (positively excited, negatively excited, and calm) of the valence-arousal coordinate based on statistical features of the frequency bands theta, alpha, beta, and gamma. In the study carried out by Murugappan et al.(2011), EEG signals were acquired from 64 electrodes to recognize five discrete video elicited emotions based on entropy features of the frequency bands delta, theta, alpha, beta, and gamma. Due to difference in experimental setups and choice of features, it might be difficult to come out with a clear and concise conclusion or a model for EEG emotion recognition based on findings from studies like these.

Based on this fact, some researchers have conducted analysis on benchmark EEG datasets in order to compare techniques and methods used in implementing EEG emotion recognition with other studies using the same dataset. The aim of using different feature sets, algorithms, and techniques on the same dataset is to compare the results in order to note the combination of feature sets and techniques that works well in EEG signal processing. Inspired by this, the present study aimed at performing analysis on a benchmark EEG signal dataset from the DEAP (A Database for Emotion Analysis Using Physiological Signals) database (Koelstra et al., 2012). DEAP is a multimodal dataset containing physiological signals and targeted emotions based on the valence-arousal model (Russel, 1980). It is expected that effective comparative analyses and more precise conclusions can be made when different methods and techniques are being applied to the same set of data.

Feature extraction is the most important process in EEG signal processing (Riera Sardà, 2012). It involves some algorithms that allow extraction of hidden information from the signals. The choice of feature extraction method is very important to accurately classify emotions using EEG signals. Due to the importance of the feature extraction process, this study aims at measuring the effect of Discrete Wavelet Packet Transform (DWPT) feature extraction method in EEG-based valence-arousal emotion recognition. DWPT is an advanced form of wavelet transform and it has recently been used in EEG signal processing to decompose EEG signals in Wali et al. (2013) and Murugappan et al. (2013) in order to classify driver distraction levels. Based on this, DWPT is proposed to be used as the feature extraction method for recognizing emotions based on the valence-arousal model by classifying human emotional states into high/low valence or high/low arousal. The benchmark dataset was used in order to compare the result of this study.

As EEG signals are acquired through multichannel electrodes, ranging from 1 to 60 useable electrode channels. Another important concern in EEG-based emotion recognition is to identify the combination of electrode channels that gives higher classification accuracy. Based on this, further experiment aiming at identifying the combination of electrode channels for EEG-based valence-arousal emotion recognition will be performed in this study.

1.4 Research Questions

This study is expected to answer the following questions.

1. How can an algorithm for DWPT feature extraction method be developed for EEG based valence-arousal emotion recognition?

2. How can the developed alogorithm be evaluated?

3. What is the combination of electrode channels that optimally recognize emotions in EEG based valence-arousal emotion recognition?

1.5 Research Objectives

The main objective of this study is to discover the feature extraction method and the combination of electrode channels that optimally implements EEG-based valence-arousal emotion recognition. The sub-objectives are;

1. To develop an algorithm for DWPT feature extraction method for EEG based valence-arousal emotion recognition.

2. To evaluate the developed algorithm.

3. To identify the combination of electrode channels that optimally recognize emotions in EEG based valence-arousal emotion recognition.

1.6 Significance of the Study

Growing number of affective computing researches have recently developed EEG-based emotion recognition systems that can recognize emotional state of human to establish affective human-computer interactions. However, there are still needs to discover methods and algorithms that will give better results. This can be achieved by using different methods, algorithms and techniques on the same dataset in order to compare the results and note the combination of feature sets and techniques that works well in EEG signal processing.

The importance of this present work is to propose DWPT as a feature extraction method and identify the combination of electrode channels that can be used with it. This result of this study is a model for EEG-based emotion recognition. Specifically adding to the effort of discovering feature extraction method and combination of electrode channels that gives best result.

1.7 Scope of the Study

The implementation of this study is based on a public EEG dataset from DEAP repository (Koelstra et al., 2012). The pre-processed version of the dataset is used, so the scope of this work would be limited to this dataset. The target emotions to be identified are the two classes of valence (high/low) and the two classes of arousal (high/low).

1.8 Organization of the Report

The report is organized into five chapters. The description of each chapter is as follows.

Chapter One presents an introduction to this research. It presents the problem that the research wants to address. It also describes the research questions and objectives. The significance and scope of this research are also discussed.

Chapter Two discusses about the review of literatures. It provides descriptions and discussions of the issues related to the research. The discussions lead to the findings in this research.

Chapter Three discusses about the methodology used in this research. It presents the design of the experiments and explanation on how the experiments were performed.

In Chapter Four, the results of the experiments performed in this research are presented and the results were compared with previous related study.

In Chapter Five, conclusions are made based on the results of this research and finally future research plans are described.

1.9 Chapter Summary

This chapter introduces the background of this study and also presents the problem that the study wants to address. Subsequently the research questions and objectives are laid down in order to address the problems. The significance and scope of this study are also discussed in this chapter.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter discusses each of the five stages involved in EEG-based emotion recognition and the methods and techniques that have been used in each stage. The dataset used in this study together with the previous studies carried out using this dataset were also discussed.

2.2 EEG-Based Emotion Recognition Process

In order to recognize emotions, researches have been carried out using valence-arousal model as the basis of emotion classification (Bos, 2007; Chanel et al., 2006; Kwon, Ahn, Hong, Park, Park, and Jun, 2013; Lin et al., 2010; Stickel, Ebner, Steinbach-Nordmann, Searle, and Holzinger, 2009). First, raw EEG data are collected either by experiments or via databases. The raw EEG data will then be pre-processed, next is extracting necessary features followed by feature selection and lastly is classification. Figure 2.1 shows these steps and all the stages are elaborated as follows.

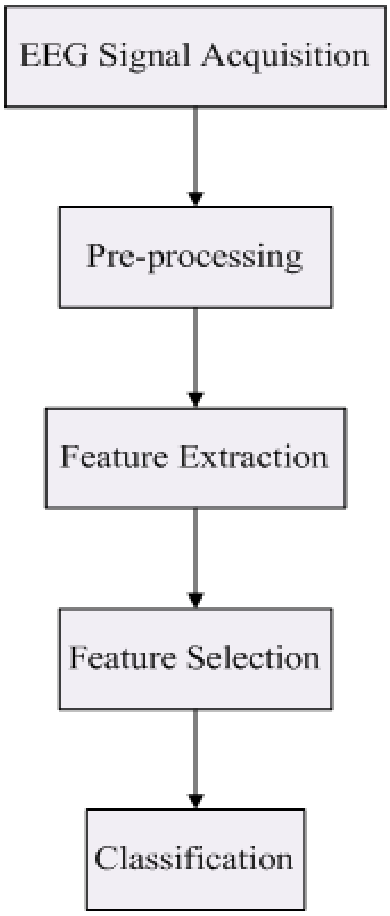


Figure 2.1. EEG-Based Emotion Recognition Process

2.2.1 EEG Signal Acquisition Phase

Researchers perform experiments that are aimed at achieving some objectives. Number of electrodes used in experiments varies from 1 to 64 electrode channels or more according to the aim of the experiment. Some researchers made these EEG data available in public databases. There are few EEG databases that are publicly available for emotion analysis. Mentioned in this study are Koelstra et al. (2012), Savran et al. (2006), Soleymani et al. (2012), and Yazdani et al. (2012). Further details are presented in Table 2.1.

The Koelstra et al., 2012 database (DEAP) also comprises of EEG and some other physiological signals. 32 subjects participated in the experiments and 40 music videos were used to induce emotions, the emotion recognition was based on the Valence-Arousal-Dominance emotion model. EEG signals were recorded from 32 channels with sampling rate of 512 Hz.

Table 2.1: *EEG Public Databases*

No.	Author / Year	Modalities	Subjects	Channels	Stimuli	Targeted Emotions
1.	Koelstra et al., 2012 (DEAP)	EEG & Peripheral data	32	32	Music Videos	Valence-Arousal-Dominance
2.	Savran, et al., 2006 (eNTERFACE)	EEG & Peripheral data	5	64*	IAPS Pictures	Calm, exciting positive & exciting negative
3.	Soleymani et al., 2012 (MAHNOB-HCI)	EEG & Peripheral data	27	32	Videos	Valence-Arousal-Dominance
4.	Yazdani et al., 2012	EEG & Peripheral data	6	32	Music Videos	Valence-Arousal

* 10 frontal electrode were later removed, remaining 54 electrodes.

The Savran et al. (2006) database (eNTERFACE Project-7) comprises of EEG and some other physiological signals including fNIRS signals. 5 subjects participated in the experiment and the stimuli used to induce emotions are pictures from IAPS, the targeted emotions are calm, exciting positive and exciting negative. EEG signals were recorded from 64 channels with sampling rate of 1024 Hz. The fNIRS sensor was placed on the frontal region, and due to the occlusion from the fNIRS sensor, EEG data acquired from AF7, AF8, AFz, Fp1, Fp2, Fpz, F5, F6, F7, and F8 were removed.

The Yazdani et al. (2012) database comprises of EEG and some other physiological signals. 6 subjects participated in the experiment and the stimuli used to induce emotions are music videos, the emotion recognition was based on the Valence-Arousal model. EEG signals were recorded from 32 channels with sampling rate of 512 Hz.

The Soleymani et al. (2012) database (MAHNOB-HCI, Experiment-1) comprises of EEG and some other physiological signals. 27 subjects participated in the experiments and 20 videos were used to induce emotions, the emotion recognition was based on the Valence-Arousal-Dominance emotion model. EEG signals were recorded from 32 channels with sampling rate of 256 Hz.

Comparing the databases, the DEAP database has some advantages over others and they are listed as follows:

- An initial experiment was done to choose the stimuli.
- Large participants; it has a large amount of subjects, that is 32 subjects.
- A total 40 music videos were used, leading to 40 trials for each subject.
- This dataset has been used by other researchers for comparative analyses.
- The frontal channels were removed from eNTERFACE.

2.2.2 Pre-Processing Phase

Due to the method of acquisition of the EEG signals from the brain, there is need to pre-process these signals before use. Pre-processing involves application of filters to remove artefacts, like eye blinking and noises due to electronic amplifier, interference from power cables or other external interference so as to get cleaner signals. Murugappan, Rizon, Nagarajan, Yaacob, Hazry, and Zunaidi, (2008) uses Average Mean Reference (AMR) to reduce the signal noise. Surface Laplacian (SL) filter has also been used to remove artefacts and noise by Murugappan, Nagarajan, and Yaacob (2011).

2.2.3 Feature Extraction Phase

In emotion recognition, the features are the characteristics of EEG signals that help in distinguishing different emotions (Hosseini, and Khalilzadeh, 2010). Feature extraction is the process of extracting necessary features from the cleaned EEG signals. It involves some algorithms that allow extraction of hidden information from signals and it is regarded as the most important process in EEG signal processing (Riera Sardà, 2012).

The choice of feature extraction approach is very important to accurately classify emotions using EEG signals. Feature extraction approaches that have been implemented in EEG emotion recognition can be categorized into three. One approach is the use of time domain analyses such as statistical parameters like mean, standard deviation, variance, and power. Other time domain analyses are Fractal Dimension (FD), Hjorth parameters, and Event Related Potentials (ERP). A second approach is the use of frequency domain analysis. Frequency domain features like Band Power can be extracted using Fourier Transform (FT) and Discrete Fourier Transform (DFT) or by computing the Power Spectral Density (PSD). The third approach is the Time-Frequency domain analysis. Time-Frequency domain features like energy and entropy can be extracted using techniques such as the Discrete Wavelet Transform (DWT).

Time domain analysis such as the statistical parameters and frequency domain analysis such as FT and DFT are regarded as linear analysis (Hosseini and Khalilzadeh, 2010). Some researchers have used linear analysis, whereas linear analysis only preserves the power spectrum but destroys the spike wave structure (Liu et al., 2011). FT and DFT were also not able to deal with non-stationary signals because they miss local changes in high frequency components while considering the whole time domain (Singh et al., 2012).

Considering the non-linearity and non-stationary properties of the EEG signals, some researchers have used Fractal Dimension (FD) and Discrete Wavelet Transform (DWT). FD is found to be suitable for the analysis of non-linear systems (Hosseini, and Naghibi-Sistani, 2009; Hosseini, and Khalilzadeh, 2010; Liu et al., 2011). DWT has also been found to be suitable for non-stationary and time-varying signals as it allows simultaneous time and frequency signal analysis and it has been successfully used by Murugappan et al. (2008), Murugappan et al. (2009), and Murugappan et al. (2011) with promising results. Discrete Wavelet Packet Transform (DWPT) which is an advance form of the DWT has recently been used in EEG signal processing.

DWPT was used to decompose EEG signals in Wali et al. (2013) and Murugappan et al. (2013) in order to classify driver distraction levels.

The result from Murugappan, Nagarajan, and Yaacob (2011) shows that entropy features captures the non-linearity of the EEG signals over different emotions better than other linear statistical features like power, standard deviation, and variance. The result from Rached and Perkusich (2013) also shows that entropy features give higher accuracy than the energy features.

2.2.4 Feature Selection Phase

Feature selection also called dimensionality reduction is necessary before performing classification. Choice of feature set plays a major role in emotion recognition (Singh et al., 2012). The features that would be used for EEG emotion recognition needs to be carefully and systematically chosen due to the fact that EEG signals are multichannel and complex signals. In feature selection, the extracted features are analyzed so as to understand as well as extract a subset of the features by removing redundant features and maintaining only the informative features. The result will be the feature vectors which can be used for classification analysis.

Feature selection techniques involve some computational algorithms like Principal Component Analysis (PCA) and Genetic Algorithm (GA). Statistical analysis like F-score Index has also been used for feature selection. Lin et al. (2010) has used F-score index for feature reduction and feature selection. PCA is a standard technique used for data reduction and feature selection due to the fact that it accounts for equal information distribution among input vectors in the data set (Mazaeva, Ntuen, and

Lebby, 2001). GA has also been used by Peterson, Knight, Kirby, Anderson, and Thaut (2005), Hosseini, and Khalilzadeh (2010), Hosseini (2012), and Yang, Singh, Hines, Schlaghecken, Iliescu, Leeson, and Stocks (2012).

Unlike other works that based feature selection by applying algorithms on the data, the selection of features used in this work are obtained from emotion classification research findings from previous literatures.

2.2.5 Classification Phase

Classification of these features can be done based on the similarity in their patterns. Techniques used in classification include K-Nearest Neighbour (KNN), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and Artificial Neural Networks (ANN). SVM is the most popularly used as EEG signal classifier (Jatupaiboon, Pan-ngum, and Israsena, 2013). Li and Lu (2009) achieved an accuracy of 93.5% with SVM for classification of two emotional state; happiness and sadness. Although SVM is a linear system, but by adding the kernel function, it can be used in a non-linear system (Sanei and Chambers, 2008). Artificial Neural Network (ANN) is another commonly used classifier. Self-Organizing Map (SOM) (Gráfová, Vyšata, and Procházka, 2010) and Multilayer Perceptron with Back-Propagation (MLP-BP) are some kind of ANN that has been used for EEG signals classifying. MLP-BP was used by Rached and Perkusich (2013) to classify EEG signals into four emotional states and recorded a highest classification accuracy of 95.56%.

2.3 DEAP EEG Dataset Details

The dataset used in this study is the EEG dataset from the DEAP database (Koelstra et al., 2012). EEG signals and other physiological signals were acquired in this experiment. This study is only interested in the EGG signals. The EEG database consists of signals recorded from 32 subjects while watching music video. The signals were recorded in 40 trials of experiments for each subject, that is, each participant was asked to watch 40 music videos. The participant were asked to rate their emotional state based on the video after each trial. The questionnaire used for the ratings is the Self-Assessment Manikins (SAM), presented in Figure 2.2. SAM contains four different type of emotional states ratings; arousal, valence, dominance and liking. The ratings utilize a continuous scaling from 1 to 9. The participants were asked to click on anywhere on or between the manikins in order to make the ratings continuous. The dataset was then preprocessed and a version was made available in MATLAB format. The MATLAB preprocessed version is used in this work.

2.3.1 MATLAB Pre-Processed DEAP EEG Dataset Description

The EEG dataset was pre-processed by Koelstra et al. (2012) as follows: the data was down-sampled from 512Hz to 128Hz. The EOG artefacts were removed and the signals were filtered by applying a band-pass frequency filter, producing a signal with frequency range 4-45Hz. The data was averaged to the common reference.

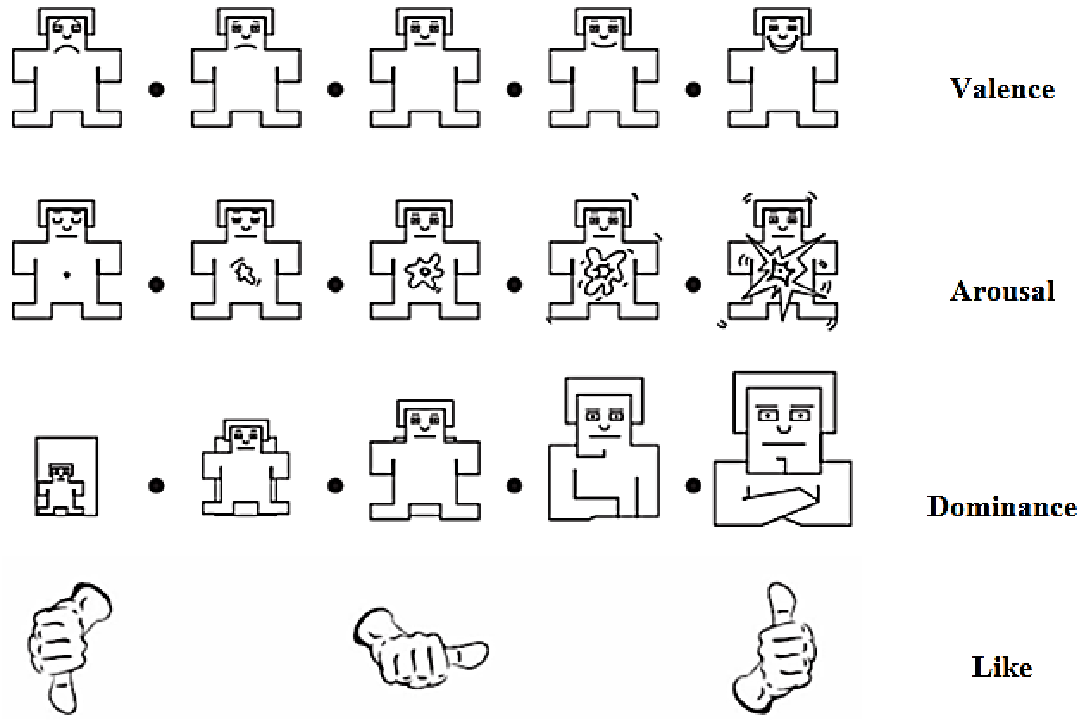


Figure 2.2. Self-Assessment Manikins (SAM) Questionnaire

Each participant's file contains two arrays: the EEG data file and the labels data file. The EEG data for each of the 32 subjects were stored in a 3-dimensional array of size (40×40×8064). Table 2.2 shows more details about the content of the files. The electric potential values 8064 are a span of 1 minute experiment. There are 40 trials of the experiment for each participant and there are 40 electrode channels used, but only the first 32 are for EEG recordings as illustrated in Table 2.3 and Figure 2.3.

Table 2.2: *DEAP EEG Dataset Description*

Array name	Array shape	Array contents
Data	40 x 40 x 8064	video/trial x channel x values
Labels	40 x 4	video/trial x label (valence, arousal, dominance, liking)

Table 2.3: *List of the 32 EEG Electrode Channels*

Channel no.	Channel
1	Fp1
2	AF3
3	F3
4	F7
5	FC5
6	FC1
7	C3
8	T7
9	CP5
10	CP1
11	P3
12	P7
13	PO3
14	O1
15	Oz
16	Pz
17	Fp2
18	AF4
19	Fz
20	F4
21	F8

22	FC6
23	FC2
24	Cz
25	C4
26	T8
27	CP6
28	CP2
29	P4
30	P8
31	PO4
32	O2

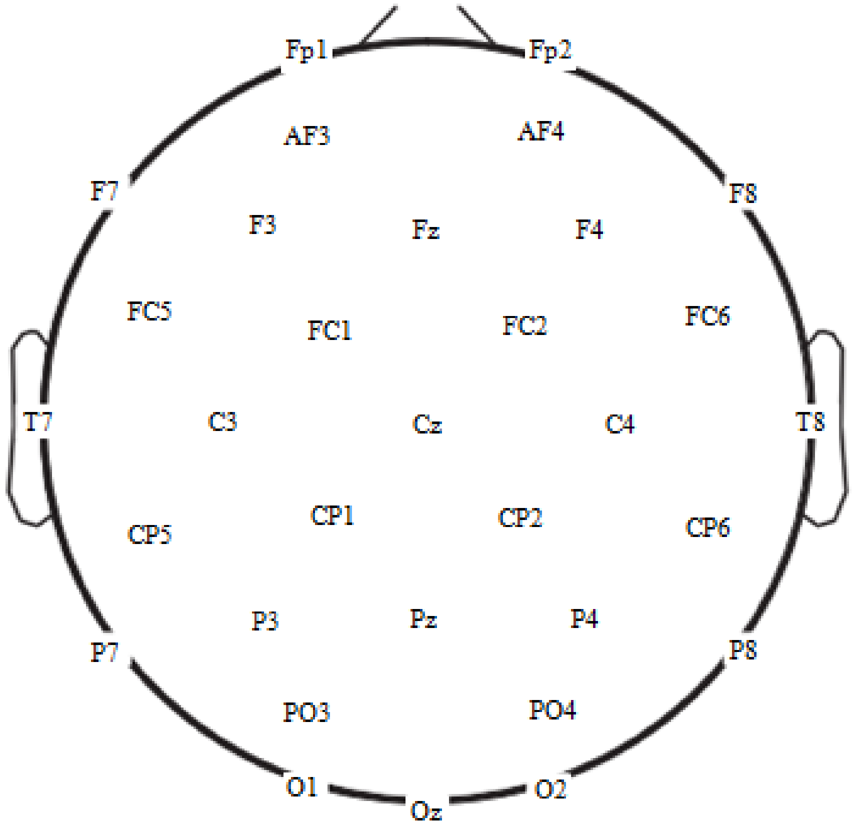


Figure 2.3. 32 Electrode Channels Location

The ratings data file is named Labels; it is a two dimensional data file (40x4). This work is concerned with only the first two columns (valence, arousal) as illustrated in Table 2.2. The ratings of the subjects on each trail represent the targets for supervised classification. Figure 2.4 shows the content of the first subject's label file. Each row represents the ratings for participant's emotional state done after each trial.

labels <40x4 double>

	1	2	3	4
1	7.7100	7.6000	6.9000	7.8300
2	8.1000	7.3100	7.2800	8.4700
3	8.5800	7.5400	9	7.0800
4	4.9400	6.0100	6.1200	8.0600
5	6.9600	3.9200	7.1900	6.0500
6	8.2700	3.9200	7	8.0300
7	7.4400	3.7300	7.0800	7.0400
8	7.3200	2.5500	6.3200	5.8700
9	4.0400	3.2900	3.6200	5.9900
10	1.9900	4.8600	2.0400	7.0900
11	2.9900	2.3600	3.6300	6.2400
12	2.7100	2.7700	3.4000	7.3500
13	1.9500	3.1200	2.8700	6.1800
14	4.1800	2.2400	3.0400	5.0400
15	3.1700	8.0800	2.9100	5.0400
16	6.8100	7.4400	8.1500	7.1400

Figure 2.4. Content of Subject 1's 40 trials label

2.3.2 Previous Works on Emotion Recognition Using DEAP EEG Dataset

Koelstra et al. (2012) performed a single trial classification on the dataset whereby all the 32 EEG electrode channels plus the 14 symmetric pairs were used for the analysis. After extracting theta, alpha, beta, and gamma spectral power using Welch's method, Naïve Bayes (NB) was used to implement a leave-one-out cross-validation classification experiment. An accuracy of 57.60 % was achieved for classifying emotion into low/high valence and 62.00 % for low/high arousal. The F1-scores were also calculated, 0.563 was achieved for classifying emotion into low/high valence and 0.583 for low/high arousal.

Bahari ans Janghorbani (2013) applied Recurrence Plot Analysis (RPA) on the dataset to extract non-linear features from all the 32 electrode channels. KNN was used to implement a leave-one-out cross-validation classification experiment and an accuracy of 58.05% was achieved for classifying emotion into low/high Valence and 64.56% for low/high Arousal.

Naser and Saha (2013) applied DT-CWPT on the dataset to extract delta, theta, beta, and gamma energy features from all the 32 EEG electrode channels plus the 14 symmetric pairs. SVM was used to implement a leave-one-out cross-validation classification experiment and an accuracy of 64.30% was achieved for classifying emotion into low/high Valence and 66.20% for low/high Arousal.

Theta, alpha, beta, and gamma spectral power features were extracted from all the 32 EEG electrode channels plus the 14 symmetric pairs by Rozgić, Vitaladevuni, and Prasad (2013). RBF-SVM was used to implement a leave-one-out cross-validation classification experiment and an accuracy of 76.90% was achieved for classifying emotion into low/high Valence and 68.40% for low/high Arousal.

Theta, alpha, beta, and gamma spectral power features were extracted from all the 32 EEG electrode channels plus the 14 symmetric pairs by Zhuang, Rozgi, and Crystal (2014). RBF-SVM was also used to implement a leave-one-out cross-validation classification experiment and an accuracy of 70.90% was achieved for classifying emotion into low/high Valence and 67.10% for low/high Arousal.

Theta, alpha, beta, and gamma band power features were also extracted from the Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 channels by Wichakam and Vateekul (2014). RBF-SVM was used to implement a leave-one-out cross-validation classification experiment and an accuracy of 64.90% was achieved for classifying emotion into low/high Valence and 65.00% for low/high Arousal. The F1-scores were also calculated, 0.514 was achieved for classifying emotion into low/high Valence and 0.508 for low/high Arousal.

The result from the study carried out by Wichakam and Vateekul (2014) for analyzing the feature extraction method shows that bandpower method is better than the PSD by wavelet transform method for valence-arousal model based EEG emotion recognition. Based on this result, the present study aimed at applying DWPT for extracting entropy features and comparing the result with that of Wichakam and Vateekul (2014). Entropy features extracted by DWPT is proposed based on the findings from the review of literatures presented in section 2.2.3.

Another conclusion that can be made from the study carried out by Wichakam and Vateekul (2014) in identifying the combination of electrode channels is that the 10 channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 gives better accuracy than using all the 32 channels for valence-arousal model based EEG emotion recognition. Based on this finding, the present study will perform a further experiment to compare the combination of the 10 channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 used in Wichakam and Vateekul (2014) with the combination of 4 frontal channels Fp1, Fp2, F3, and F4 used in Bastos-Filho, Ferreira, Atencio, Arjunan, and Kumar (2012), Singh, Jati, Khasnobish, Bhattacharyya, Konar, Tibarewala, and Janarthanan (2012), and Petrantonakis and Hadjileontiadis (2010).

In summary, two classification experiments will be performed in the study. The first experiment is to compare the result of entropy features extracted by DWPT with the bandpower features extracted by Wichakam and Vateekul (2014). The second experiment is to compare the combination 4 frontal channels Fp1, Fp2, F3, and F4 with that of the combination of 10 channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2.

The following sections discuss DWPT as a feature extraction method and RBF-SVM as a classifier. The implementation of emotion classification for the two experiments is then explained in subsequent sections.

2.4 DWPT Details

DWPT is used as the feature extraction technique; it is a form of DWT. The DWT is based on multi-resolution analysis of wavelet transform and it is the method of repeatedly filtering a given signal with two filters; a high band-pass filter and low band-pass filter, which cut the frequency domain in the middle. Subsequently DWT decomposes the signal into an approximation (A) and detailed signal (D) corresponding to different frequency ranges, while conserving the time information of the signal**.** The resulting approximation signal is further divided into new approximation and detailed signal.

The difference between DWT and DWPT is that DPWT can further decompose the detailed signals whereas the DWT only decompose the resulting approximation signals into new approximation and detailed signal, as illustrated in Figure 2.5 and Figure 2.6. This reason gives DWPT preference over DWT.

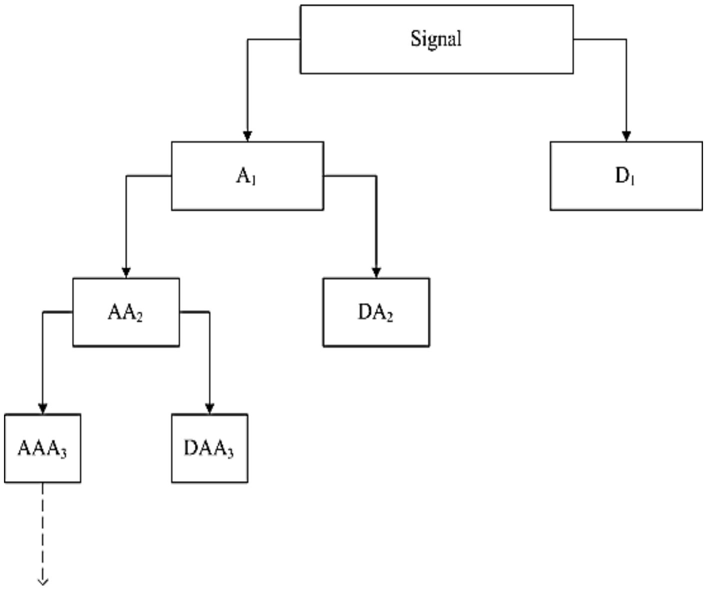


Figure 2.5. 3-level DWT decomposition

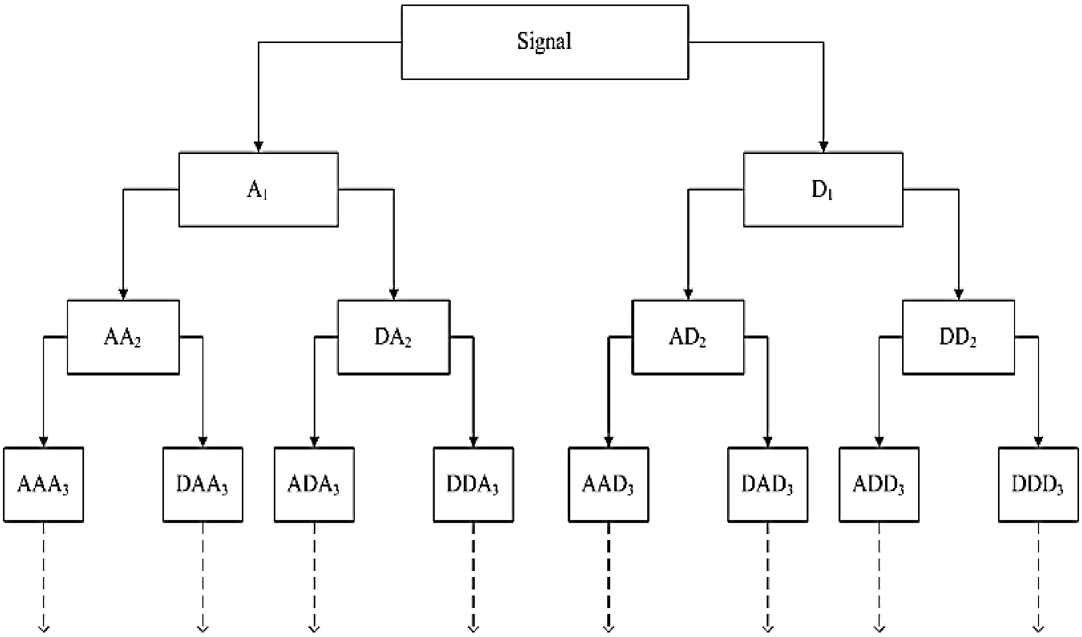


Figure 2.6. 3-level DWPT decomposition

2.5 RBF-SVM Details

In order to match experimental conditions with Wichakam and Vateekul (2014), RBF-SVM was used as the classifier in this work. SVM is a supervised classification technique. It was first proposed in 1979 by Vapnik (Sanei and Chambers, 2008). Since then, it has been a famous technique that has been used in analyzing data and pattern recognition. SVM is able to deal with small data samples and has an effective generalization capability. It is also good for data with unbalanced class targets (Jie, Cao, and Li, 2014).

2.5.1 SVM as A Linear Classifier

Considering a linearly separable data having training examples with two classes, SVM is able to build a model based on the training data that assigns new data into the one of the two classes. The concept of SVM model is based on finding the best hyper-plane, that is, a gap that is as wide as possible to separate all the data points of one class from those of the other class, as illustrated in Figure 2.7.

Let a training dataset, *D*, represented by a set of *n* points in space in the form

$$\mathcal{D} = \left\{ (\mathbf{x}_i, y_i) \mid \mathbf{x}_i \in \mathbb{R}^p,\ y_i \in \{-1, 1\} \right\}_{i=1}^{n}$$

x_i is assigned to one of the two binary classes with corresponding labels $y_i = \pm 1$. Each x_i is a p-dimensional real vector.

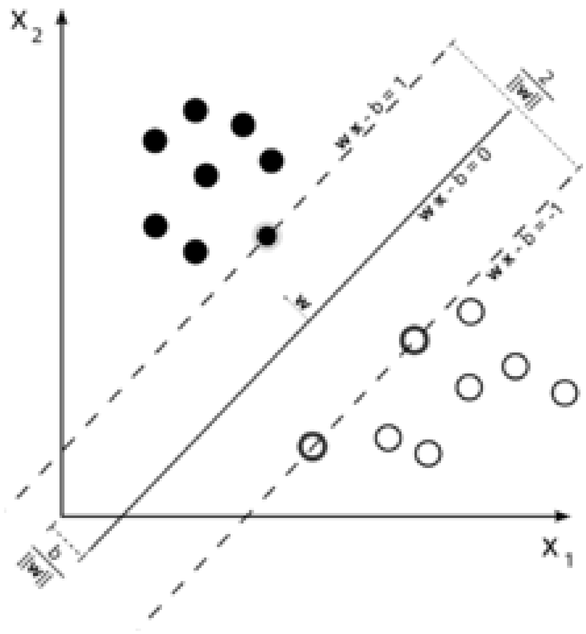


Figure 2.7. SVM as A Linear Classifier with the Separating Hyperplane.

Introducing two hyperplanes that are able to separate the data so that there are no points between them, the region between these two lines is referred to as the 'margin', and the data points that are closest to the hyperplanes are referred to as the support vectors. The concept is to find a maximum margin that divides the points having y_i = 1 from those having y_i = -1. Any hyperplane can be written as the set of points x satisfying

$$\mathbf{w} \cdot \mathbf{x} - b = 0,$$

Where the period (.) denotes the dot product and w is a normal vector to the hyperplane. The equations of these two hyperplanes are

$$\mathbf{w} \cdot \mathbf{x} - b = 1 \text{ and } \mathbf{w} \cdot \mathbf{x} - b = -1.$$

And the distance between these two hyperplanes is $\frac{2}{\|\mathbf{w}\|}$. Therefore, maximizing distance between these two hyperplanes is equivalent to minimizing $\|\mathbf{w}\|$. By adding a constraint in order to prevent the data points from falling into the margin; for each class either

$$\mathbf{w}\cdot\mathbf{x}_i - b \geq 1 \qquad \text{for } \mathbf{x}_i \text{ (of the first class)}$$

or

$$\mathbf{w}\cdot\mathbf{x}_i - b \leq -1 \qquad \text{for } \mathbf{x}_i \text{ (of the second.)}$$

Both of these constraints are written as:

$$y_i(\mathbf{w}\cdot\mathbf{x}_i - b) \geq 1, \quad \text{for all } 1 \leq i \leq n. \qquad (1)$$

The optimization problem can be written as a quadratic programming optimization problem;

$$\min_{w,b} \frac{1}{2}\|w\|^2$$

subject to: $y_i(\mathbf{w}\cdot\mathbf{x_i} - b) \geq 1$ (for any $i = 1, \ldots, n$)

2.5.2 Soft Margin Extension

Considering a non-perfectly linearly separable data, a soft margin is introduced in order to allow some data points of one class to appear on the other side of the boundary, as illustrated in Figure 2.8. This is implemented by introducing slack variables, $\xi_i \geq 0$, which measure the degree of misclassification of the data x_i.

$$y_i(\mathbf{w} \cdot \mathbf{x_i} - b) \geq 1 - \xi_i \quad 1 \leq i \leq n.$$

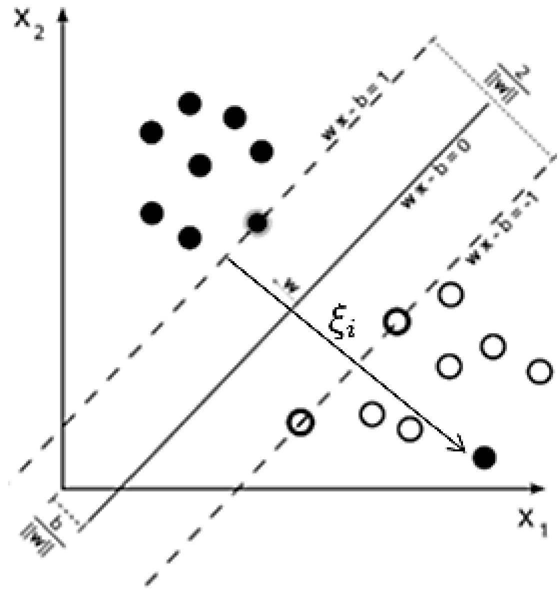


Figure 2.8. SVM as A Linear Classifier with the Soft Margin Extension

The quadratic programming problem becomes

$$\min_{w,b,\xi} \left\{ \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i \right\}$$

subject to: $y_i(\mathbf{w} \cdot \mathbf{x_i} - b) \geq 1 - \xi_i, \quad \xi_i \geq 0$ (for any $i = 1, \ldots n$)

The constant *C* is a penalty parameter. Increasing *C* places more weight on the slack variables ξ_i, meaning the optimization attempts to make a stricter separation between the classes. Also reducing *C* towards 0 makes misclassification less important.

2.5.3 SVM as a Non-linear classifier

Although SVM is a linear system, however, by adding the kernel function it can be used in a non-linear system. This is added in order to attain maximum-margin hyperplanes. The resulting quadratic programming problem is similar to the former only that all dot product is replaced by a nonlinear kernel function. Table 2.4 presents two common SVM kernels, which are the Polynomial and the Gaussian Radial Basis Function (RBF).

Table 2.4: *Common Kernels for SVM*

No	Kernel	Function
1	Polynomial	$k(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i} \cdot \mathbf{x_j} + 1)^d$, for d > 0.
2	RBF	$k(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\gamma \lVert \mathbf{x_i} - \mathbf{x_j} \rVert^2)$, for $\gamma > 0$. Where $\gamma = 1/2\sigma^2$

2.5.4 Parameter Selection

There are three parameters to be chosen for the optimization of an SVM classifier. These parameters are the kernel, the kernel's parameters, and soft margin parameter

C. When using the RBF kernel, two parameter gamma (γ) and C are needed to be tuned. The best combination of both parameters is often selected by performing search with exponentially growing sequences of γ and C. An example is the range $\{2^{-6},..., 2^{6}\}$ for both parameters.

2.6 Signal Processing Tool

MATLAB software is used for the processing of the EEG data. MATLAB is popular software for computation of data in a matrix form. The One-Dimensional Discrete Wavelet Packet Analysis Tool from the MATLAB Wavelet Toolbox Main Menu is used in this work to analyze the signals. A screen-print is shown in Figure 2.9.

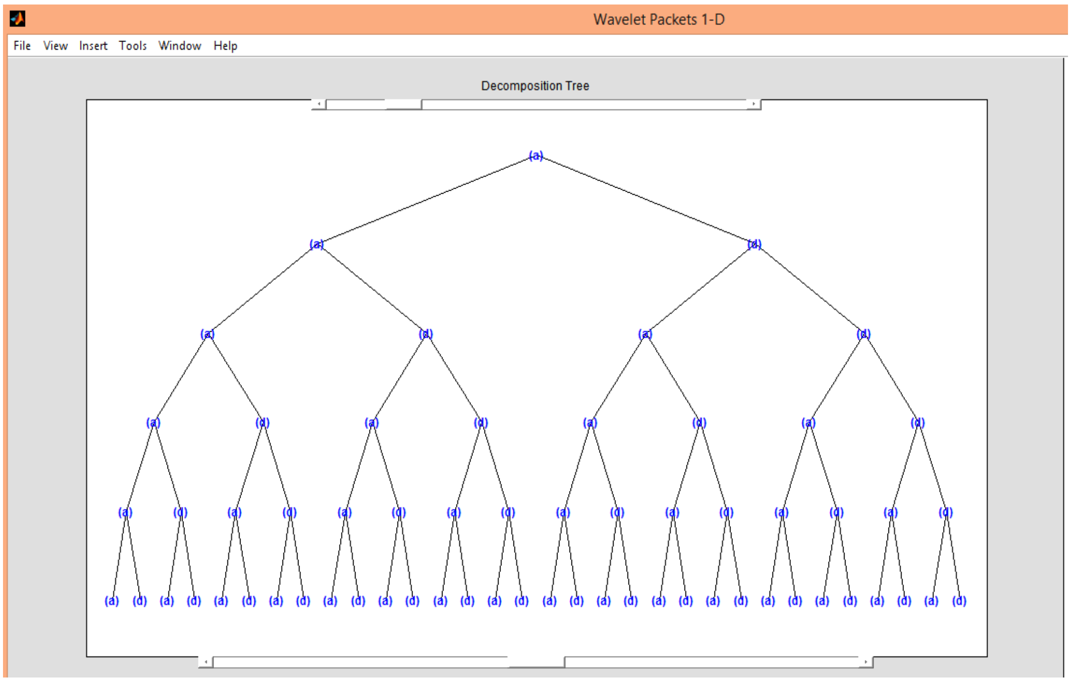


Figure 2.9. Screen-print of One-Dimensional Discrete Wavelet Packet Analysis Tool

2.7 Chapter Summary

In this chapter, EEG-based emotion recognition process was discussed and previous literatures were reviewed regarding the five stages involved in EEG-based emotion recognition process. Details about the dataset used for analyses in this study were discussed and previous literatures that have used the same dataset were reviewed.

CHAPTER THREE
METHODOLOGY

3.1 Introduction

There are three phases in this study based on the research objectives as shown in Figure 3.1. The three phases are explained in details in the following sections.

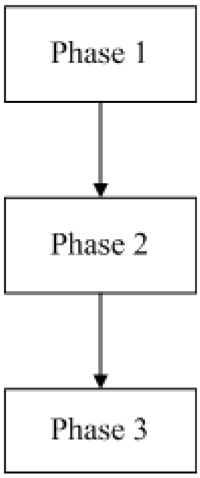


Figure 3.1. General Process of the Study

3.2 Phase 1

The aim of Phase 1 is to develop an algorithm based on DWPT to extract the theta, alpha, beta, and gamma bands from each EEG signal. After extracting these frequency bands, entropy for each extracted bands were computed. The DWPT decomposition and the computation of the entropy features were implemented using MATLAB. MATLAB function “wpdec” was used for the decomposition and “wpcoef” for calculating the coefficient. The entropy was also computed using the “wentropy” function. The output of this phase is an algorithm and the entropy values computed. The results are presented in Chapter 4, section 4.1.

Suitable level of decomposition and wavelet function need to be considered when using DWPT decomposition in order to achieve the bands needed for analysis. Daubechies wavelet function with order ‘db4’ was chosen to be used in this work based on work of Wali et al. (2013). Applying Daubechies wavelet function with order ‘db4’ for five-level DWPT decomposition of a signal, the resulting decomposition tree is presented in Figure 3.2. This technique was applied on each trial’s 10 signals representing the 10 EEG channels, in order to extract the four frequency bands, theta, alpha, beta (low beta and high beta) and gamma.

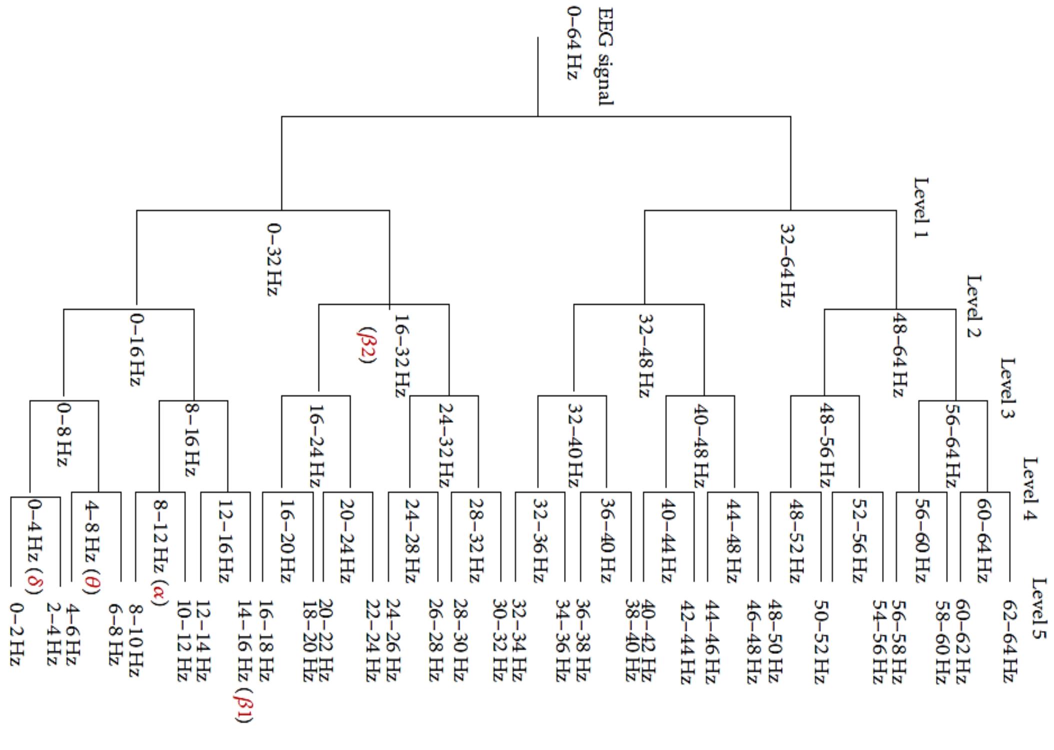


Figure 3.2. 5-Level DWPT Decomposition Tree (Wali et al., 2013)

As a result of the pre-processing of the DEAP EEG signal, whereby the signals were filtered to 4-45Hz, the delta band was not used in this work. Additionally, some researches has shown that delta band is less significant in human emotion recognition (Cabredo, Legaspi, Inventado, and Numao, 2013; Jatupaiboon, Pan-ngum, and Israsena, 2013,a; Jatupaiboon, Pan-ngum, and Israsena, 2013,b; Koelstra, et al, 2012; Wichakam and Vateekul, 2014). Details of the frequency bands and the correlated DWPT packets used are provided in Table 3.1.

Table 3.1: *Frequency Bands and Correlated DWPT Packets*

Frequency Bands (Range)*	**DWPT Packets**	**Pre-Processed DEAP EEG Signal (4-45 Hz)**	**DWPT Packets Used**
Delta (0.5-4 Hz)	0-4 Hz	No	X
Theta (4-8 Hz)	4-8 Hz	Yes	✓
Alpha (8-13 Hz)	8-12 Hz	Yes	✓
Beta (13-30 Hz)	14-16 Hz	Yes	✓
	16-32 Hz	Yes	✓
Gamma (32-45 Hz)	32-36 Hz	Yes	X
	32-40 Hz	Yes	✓
	32-48 Hz	No	X

* According to Sanei and Chambers (2008)

3.3 Phase 2

In this phase, the algorithm developed in Phase 1 was run on the DEAP dataset. The resulting entropy values form the feature vectors that were used as input for emotion classification. The results of the classification experiments were averaged over the 32 subjects. The average accuracy and F1-score are presented in Chapter 4, section 4.2.1. The results were compared with that of Wichakam and Vateekul (2014) as shown in Chapter 4, section 4.2.2.

Figure 3.3 shows the framework of the experiment in Phase 2 from loading the EEG signals to the classification stage. The flowchart is also presented in Figure 3.4.

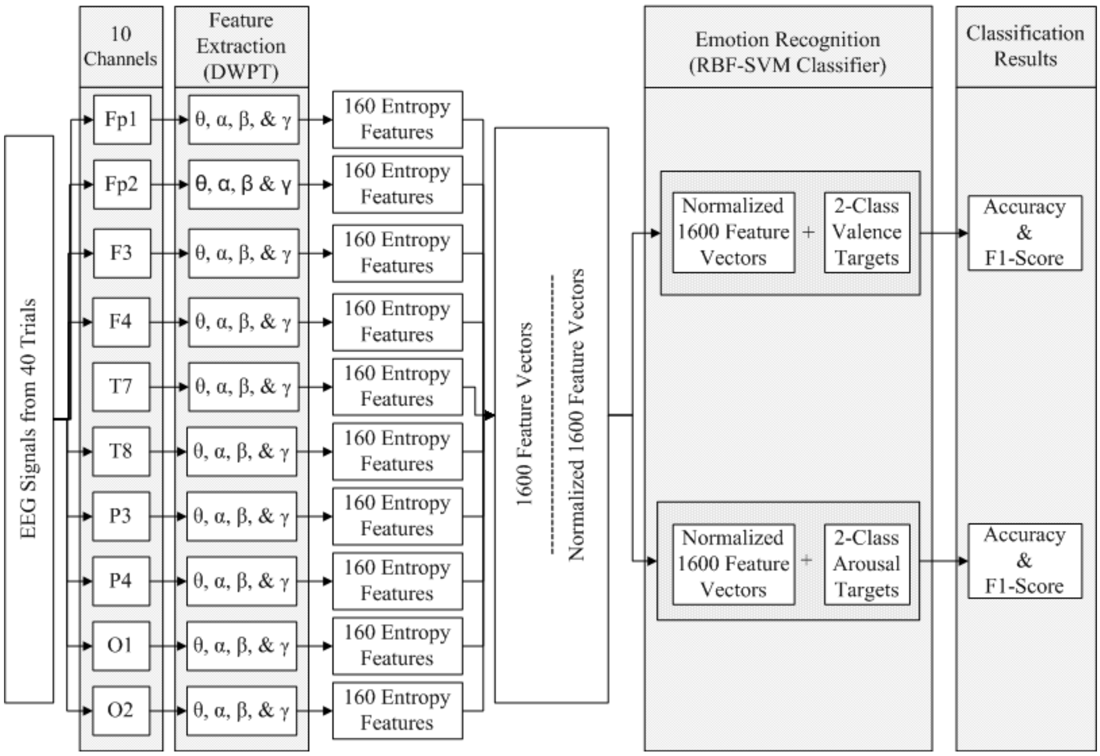


Figure 3.3. Phase 2 Framework

The EEG signal for 40 trials were loaded into MATLAB environment. The electrode channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 were selected from each trial. DWPT was applied to extract the theta, alpha, beta, and gamma bands and the entropy values were computed. Each channel presents 160 entropy features which leads to a total of 1600 feature vectors for the whole 40 trials.

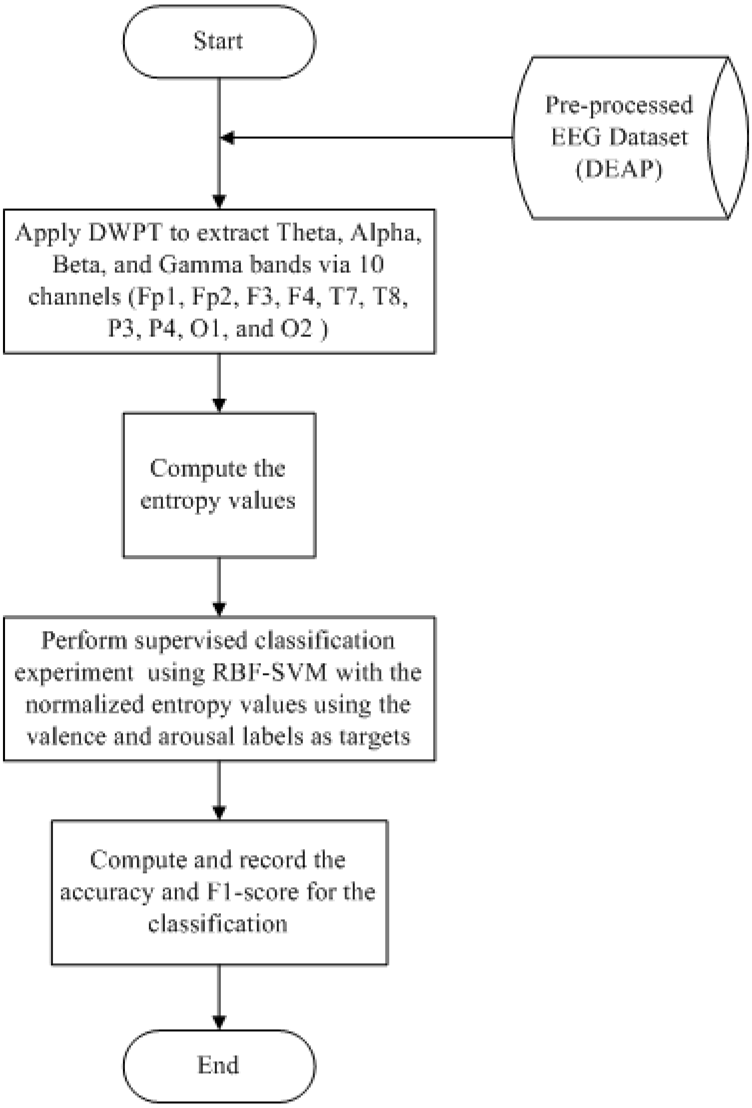


Figure 3.4. Phase 2 Flowchart

The normalized feature vectors with the classification targets were then presented to RBF-SVM classifier. A leave-one-out cross-validation classification experiment was performed on each subject's dataset. The accuracy and F1-scores were recorded. The process was repeated for all the 32 subjects and the accuracy and F1-scores were averaged. The confusion matrix is presented in Table 3.2.

Table 3.2: *Confusion Matrix for Phase 2 Classification Experiment*

Trials	**Fp1**				**Fp2**				**.**	**O2**				**Target**	**Predicted Values**
	θ	α	β	γ	θ	α	β	γ	.	θ	α	β	γ		
1	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
7	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
8	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	.	-	-	-	-	-	-
.															
.															
.															
40	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Each subject's data is a 40x41 2-dimesntional data. The 40 rows represent the number of trials. The first 40 columns are for the feature vectors and column number 41 is for the class targets. The ratings of the subjects based on the valence and arousal levels for each trail are used as the classification targets, as discussed in section 2.3.1. The labels were transformed according to Koelstra et.al. (2012). The target has two classes; from 5 to 9 class for high is denoted by '1' while values lower than 5 are labeled as low and denoted by '0'. Before the classification experiment, the values of the entropy features were normalized to produce values from 0 to 1. Min-Max normalization technique was used in this work. The formula for Min-Max normalization is presented in equation 3.1.

$$X_n = \frac{X_0 - X_{min}}{X_{max} - X_{min}} \tag{3.1}$$

Where,

X_n = new value for variable X
X_0 = original value for variable X
X_{min} = minimum value of the attribute
X_{max} = maximum value of the attribute

MATLAB was used to process the normalization as well as to implement the RBF-SVM classification. Using leave-one-out cross validation, one trial was left out as the testing dataset while the remaining 39 as the training datasets were used to train the classifier and then the testing dataset is used for testing.

As the Gaussian RBF function was used as the kernel function, there is need to tune the two parameters γ and C in order to search for the best combination. The range $\{2^{-6},..., 2^{6}\}$ was utilized as the search range for both (Rozgic et al., 2013; Zhuang et al., 2014). The MATLAB functions 'svmtrain' was used to train the SVM classifier. The option 'qp' representing Quadratic Programming was chosen for the 'method' used to find the separating hyperplane. MATLAB utilizes the 'boxconstraint' for setting the value of the parameter C. The option 'rbf' representing the RBF kernel was used for the 'kernel_function'. MATLAB utilizes sigma (σ) as the scaling factor for the RBF kernel; it is represented as 'rbf_sigma'. The relationship between σ and γ is:

$$\gamma = 1/2\sigma^2$$

Experiments were carried out by applying various values of the tuning parameters σ and C. The result of the experiment gives accuracy and F1-score. The accuracy and F1-scores were recorded for each Subject's 40 trails. The formula used for computing the accuracy and F1-score is presented in equation 3.2 to 3.6. Where, the true positive, false positive, true negative, false negative were represented as TP, FP, TN, and FN respectively.

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{3.2}$$

$$Precision^{+} = \frac{TP}{TP+FP} \quad , \; Precision^{-} = \frac{TP}{TP+FP} \tag{3.3}$$

$$Recall^{+} = \frac{TP}{TP+FN} \quad , \; Recall^{-} = \frac{TP}{TP+FN} \tag{3.4}$$

$$F1^{+} = \frac{2\times Precision^{+} \times Recall^{+}}{Precision^{+}+Recall^{+}} \quad , \; F1^{-} = \frac{2\times Precision^{-} \times Recall^{-}}{Precision^{-}+Recall^{-}} \tag{3.5}$$

$$F1 = \frac{F1^{+}+F1^{-}}{2} \tag{3.6}$$

The classification experiment was first carried out using the valence targets followed by the arousal targets. Considering the imbalance nature of the classes, the F1-score values were used to choose the best parameters, due to the fact that the F1-score takes the class balance into account, contrary to the mere classification accuracy (Koelstra et.al, 2012). The first participant's classification experiment with valence targets are as follows. Table 3.3 shows the result obtained when the value for the ‘rbf_sigma’ is varied. Highest accuracy of 52.50% and F1-score of 48.61 % were obtained when the sigma value was 1.52.

Table 3.3: *Varying Sigma Values (Valence - Subject 1)*

Sigma	**Accuracy (%)**	**F1 (%)**
5.656854249	32.5	32.45778612
5.278031643	32.5	32.45778612
4.924577653	30	30
4.59479342	32.5	32.45778612
4.28709385	35	34.83709273
4	35	34.83709273
3.732131966	35	34.83709273
3.482202253	40	39.84962406
3.249009585	40	39.84962406
3.031433133	37.5	37.46091307
2.828427125	40	39.84962406
2.639015822	45	44.44444444
2.462288827	45	44.44444444
2.29739671	45	43.73401535
2.143546925	45	43.73401535
2	45	43.73401535
1.866065983	47.5	45.84139265
1.741101127	47.5	44.70046083
1.624504793	50	46.66666667
1.515716567	52.5	48.61392833
1.414213562	50	43.01994302
1.319507911	52.5	38.66020985
1.231144413	52.5	0
1.148698355	52.5	0
1.071773463	52.5	0
1	52.5	0
0.933032992	52.5	0
0.870550563	52.5	0
0.812252396	52.5	0

0.757858283	52.5	0
0.707106781	52.5	0
0.659753955	52.5	0
0.615572207	52.5	0
0.574349177	52.5	0
0.535886731	52.5	0
0.5	52.5	0
0.466516496	52.5	0
0.435275282	52.5	0
0.406126198	52.5	0
0.378929142	52.5	0
0.353553391	52.5	0
0.329876978	52.5	0
0.307786103	52.5	0
0.287174589	52.5	0
0.267943366	52.5	0
0.25	52.5	0
0.233258248	52.5	0
0.217637641	52.5	0
0.203063099	52.5	0
0.189464571	52.5	0
0.176776695	52.5	0
0.164938489	52.5	0
0.153893052	52.5	0
0.143587294	52.5	0
0.133971683	52.5	0
0.125	52.5	0
0.116629124	52.5	0
0.10881882	52.5	0
0.10153155	52.5	0
0.094732285	52.5	0
0.088388348	52.5	0

While the sigma value was fixed to 1.52, the C parameter value was varied. Table 3.4 shows the result. Highest accuracy of 55.00% and F1-score of 50.55% were obtained when the C values were from 0.016 to 0.66.

Table 3.4: *Varying the C parameter Values (Valence – Subject 1)*

C	Accuracy (%)	F1 (%)
0.015625	55	50.54945055
0.017948412	55	50.54945055
0.020617311	55	50.54945055
0.023683071	55	50.54945055
0.027204705	55	50.54945055
0.03125	55	50.54945055
0.035896824	55	50.54945055
0.041234622	55	50.54945055
0.047366143	55	50.54945055
0.05440941	55	50.54945055
0.0625	55	50.54945055
0.071793647	55	50.54945055
0.082469244	55	50.54945055
0.094732285	55	50.54945055
0.10881882	55	50.54945055
0.125	55	50.54945055
0.143587294	55	50.54945055
0.164938489	55	50.54945055
0.189464571	55	50.54945055
0.217637641	55	50.54945055
0.25	55	50.54945055
0.287174589	55	50.54945055
0.329876978	55	50.54945055
0.378929142	55	50.54945055
0.435275282	55	50.54945055
0.5	55	50.54945055
0.574349177	55	50.54945055
0.659753955	55	50.54945055
0.757858283	52.5	48.61392833

0.870550563	52.5	48.61392833
1	52.5	48.61392833
1.148698355	52.5	48.61392833
1.319507911	52.5	48.61392833
1.515716567	52.5	48.61392833
1.741101127	52.5	48.61392833
2	52.5	48.61392833
2.29739671	52.5	48.61392833
2.639015822	52.5	48.61392833
3.031433133	52.5	48.61392833
3.482202253	52.5	48.61392833
4	52.5	48.61392833
4.59479342	52.5	48.61392833
5.278031643	52.5	48.61392833
6.062866266	52.5	48.61392833
6.964404506	52.5	48.61392833
8	52.5	48.61392833
9.18958684	52.5	48.61392833
10.55606329	52.5	48.61392833
12.12573253	52.5	48.61392833
13.92880901	52.5	48.61392833
16	52.5	48.61392833
18.37917368	52.5	48.61392833
21.11212657	52.5	48.61392833
24.25146506	52.5	48.61392833
27.85761803	52.5	48.61392833
32	52.5	48.61392833
36.75834736	52.5	48.61392833
42.22425314	52.5	48.61392833
48.50293013	52.5	48.61392833
55.71523605	52.5	48.61392833
64	52.5	48.61392833

The first participant's classification experiment with arousal targets are as follows. Table 3.5 shows the result obtained when the value for the 'rbf_sigma' is varied.

Highest accuracy of 65% and F1-score of 49.82 % were obtained when the sigma value was 1.87.

Table 3.5: *Varying Sigma Values (Arousal – Subject 1)*

Sigma	Accuracy (%)	F1 (%)
5.656854249	50	48.84910486
5.278031643	47.5	45.84139265
4.924577653	47.5	45.84139265
4.59479342	40	37.5
4.28709385	40	37.5
4	40	37.5
3.732131966	40	37.5
3.482202253	40	36
3.249009585	40	36
3.031433133	42.5	37.79580798
2.828427125	42.5	37.79580798
2.639015822	45	37.32193732
2.462288827	47.5	38.90909091
2.29739671	50	40.47619048
2.143546925	50	40.47619048
2	55	43.57366771
1.866065983	65	49.82078853
1.741101127	62.5	43.97759104
1.624504793	60	0
1.515716567	60	0
1.414213562	60	0
1.319507911	60	0
1.231144413	60	0
1.148698355	60	0
1.071773463	60	0
1	60	0
0.933032992	60	0
0.870550563	60	0
0.812252396	60	0
0.757858283	60	0
0.707106781	60	0

0.659753955	60	0
0.615572207	60	0
0.574349177	60	0
0.535886731	60	0
0.5	60	0
0.466516496	60	0
0.435275282	60	0
0.406126198	60	0
0.378929142	60	0
0.353553391	60	0
0.329876978	60	0
0.307786103	60	0
0.287174589	60	0
0.267943366	60	0
0.25	60	0
0.233258248	60	0
0.217637641	60	0
0.203063099	60	0
0.189464571	60	0
0.176776695	60	0
0.164938489	60	0
0.153893052	60	0
0.143587294	60	0
0.133971683	60	0
0.125	60	0
0.116629124	60	0
0.10881882	60	0
0.10153155	60	0
0.094732285	60	0
0.088388348	60	0

While the sigma value was fixed to 1.87 the C parameter value was varied. Table 3.6 shows the result. Highest accuracy of 65% and F1-score of 49.82 % were obtained when the C values were from 0.44 to 64.

Table 3.6: *Varying the C parameter Values (Arousal– Subject 1)*

C	Accuracy (%)	F1 (%)
0.015625	60	46.66666667
0.017948412	60	46.66666667
0.020617311	60	46.66666667
0.023683071	60	46.66666667
0.027204705	60	46.66666667
0.03125	60	46.66666667
0.035896824	60	46.66666667
0.041234622	60	46.66666667
0.047366143	60	46.66666667
0.05440941	60	46.66666667
0.0625	60	46.66666667
0.071793647	60	46.66666667
0.082469244	60	46.66666667
0.094732285	60	46.66666667
0.10881882	60	46.66666667
0.125	60	46.66666667
0.143587294	60	46.66666667
0.164938489	60	46.66666667
0.189464571	60	46.66666667
0.217637641	62.5	48.23123382
0.25	62.5	48.23123382
0.287174589	62.5	48.23123382
0.329876978	62.5	48.23123382
0.378929142	62.5	48.23123382
0.435275282	65	49.82078853
0.5	65	49.82078853
0.574349177	65	49.82078853
0.659753955	65	49.82078853
0.757858283	65	49.82078853
0.870550563	65	49.82078853
1	65	49.82078853
1.148698355	65	49.82078853
1.319507911	65	49.82078853
1.515716567	65	49.82078853
1.741101127	65	49.82078853

2	65	49.82078853
2.29739671	65	49.82078853
2.639015822	65	49.82078853
3.031433133	65	49.82078853
3.482202253	65	49.82078853
4	65	49.82078853
4.59479342	65	49.82078853
5.278031643	65	49.82078853
6.062866266	65	49.82078853
6.964404506	65	49.82078853
8	65	49.82078853
9.18958684	65	49.82078853
10.55606329	65	49.82078853
12.12573253	65	49.82078853
13.92880901	65	49.82078853
16	65	49.82078853
18.37917368	65	49.82078853
21.11212657	65	49.82078853
24.25146506	65	49.82078853
27.85761803	65	49.82078853
32	65	49.82078853
36.75834736	65	49.82078853
42.22425314	65	49.82078853
48.50293013	65	49.82078853
55.71523605	65	49.82078853
64	65	49.82078853

3.4 Phase 3

The aim of Phase 3 is to identify the combination of electrode channels that optimally recognize emotions based on the valence-arousal model in EEG emotion recognition. This was done by selecting the 4 electrode channels Fp1, Fp2, F3, and F4, which were previously used by Bastos-Filho, Ferreira, Atencio, Arjunan, and Kumar (2012), Singh, Jati, Khasnobish, Bhattacharyya, Konar, Tibarewala, and

Janarthanan (2012), and Petrantonakis and Hadjileontiadis (2010), instead of the 10 electrode channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 used in Phase 2. The classification experiment was repeated using these 4 channels. The results were averaged over the 32 subjects. The average accuracy and F1-score are presented in Chapter 4, section 4.3.1. The results were compared with that of Phase 2 as shown in Chapter 4, section 4.3.2.

Figure 3.5 shows the framework of the experiment in Phase 3 from loading the EEG signals to the classification stage. The flow chart is also presented in Figure 3.6. The EEG signal for 40 trials were loaded into MATLAB environment. The electrode channels Fp1, Fp2, F3, and F4 were selected from each trial. DWPT was applied to extract the theta, alpha, beta, and gamma bands and the entropy values were computed. Each channel presents 160 entropy features which leads to a total of 640 feature vectors for the whole 40 trials.

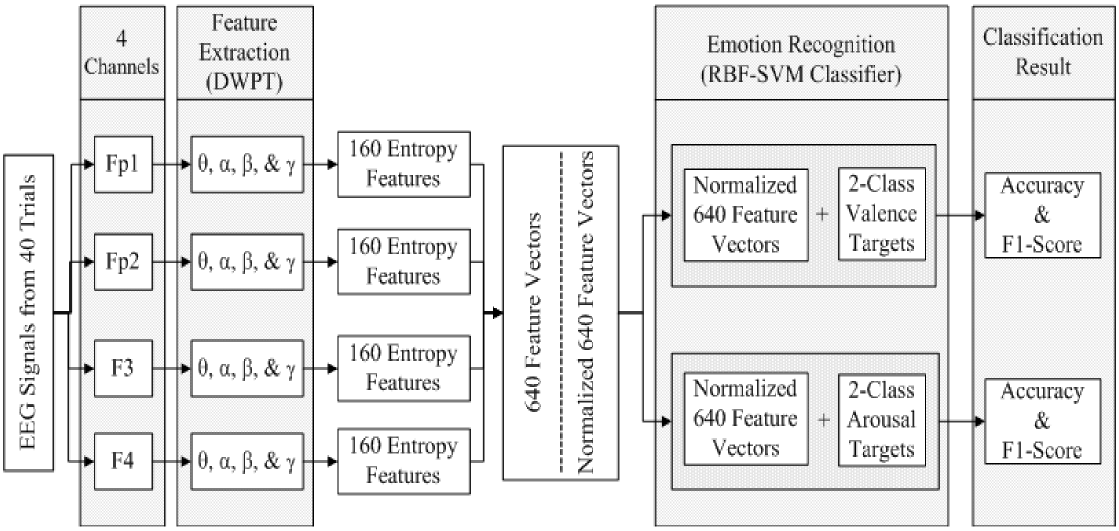


Figure 3.5. Phase 3 Framework

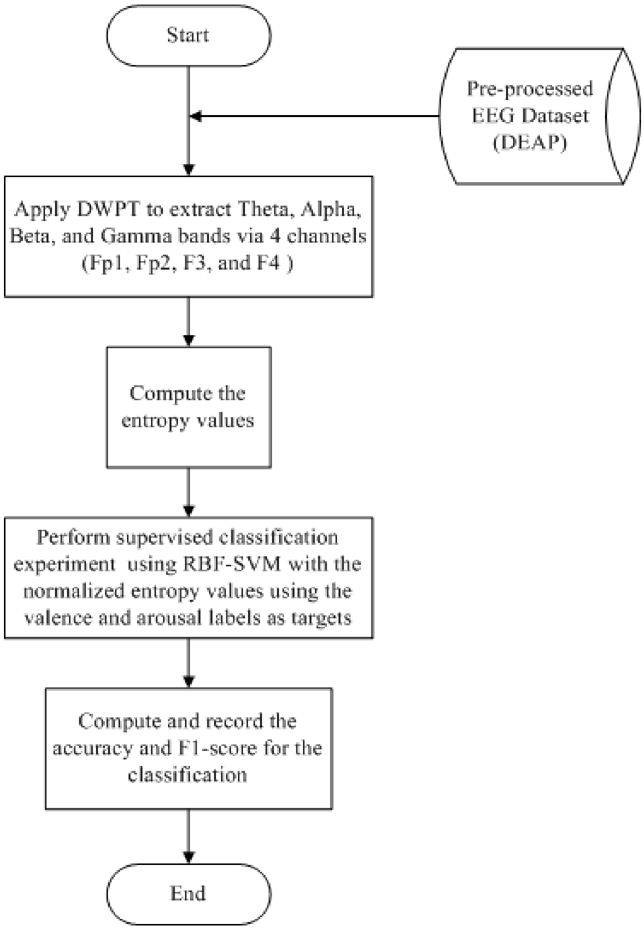


Figure 3.6. Phase 3 Flowchart

The normalized feature vectors with the classification targets were then presented to RBF-SVM classifier. A leave-one-out cross-validation classification experiment was performed on each subject's dataset. The accuracy and F1-scores were recorded. The process was repeated for all the 32 subjects and the accuracy and F1-scores were averaged. The confusion matrix is presented in Table 3.7.

Table 3.7: *Confusion Matrix for Phase 3 Classification Experiment*

Trials	**Fp1**				**Fp2**				**F3**				**F4**				**Target**	**Predicted Values**
	θ	α	β	γ	θ	α	β	γ	θ	α	β	γ	θ	α	β	γ		
1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
.																		
.																		
.																		
40	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Each subject's data is a 40x17 2-dimesntional data. The 40 rows represent the number of trials. The first 16 columns are for the feature vectors and column number 17 is for the class targets. The ratings of the subjects based on the valence and arousal levels for each trail are used as the classification targets, as discussed in section 2.3.1.

The first participant's classification experiment with valence targets are as follows. Table 3.8 shows the result obtained when the value for the 'rbf_sigma' is varied. Highest accuracy of 47.50% and F1-score of 47.47 % were obtained when the sigma value was 5.66.

Table 3.8: *Varying Sigma Values (Valence - Subject 1)*

Sigma	**Accuracy (%)**	**F1 (%)**
5.656854249	47.5	47.46716698
5.278031643	45	44.86215539
4.924577653	42.5	42.46404003
4.59479342	42.5	42.46404003
4.28709385	40	39.84962406
4	40	39.84962406
3.732131966	40	39.84962406
3.482202253	40	39.84962406
3.249009585	37.5	37.46091307
3.031433133	32.5	32.45778612
2.828427125	35	35
2.639015822	37.5	37.14644877
2.462288827	35	34.83709273
2.29739671	32.5	32.45778612
2.143546925	30	30
2	30	30
1.866065983	35	34.83709273
1.741101127	37.5	37.14644877
1.624504793	35	34.34343434
1.515716567	32.5	31.42857143
1.414213562	32.5	31.42857143
1.319507911	32.5	31.42857143
1.231144413	32.5	31.42857143
1.148698355	37.5	35.52546744
1.071773463	37.5	34.16721527
1	37.5	34.16721527
0.933032992	37.5	34.16721527
0.870550563	40	36

0.812252396	42.5	35.7092942
0.757858283	45	37.32193732
0.707106781	45	37.32193732
0.659753955	45	37.32193732
0.615572207	47.5	38.90909091
0.574349177	47.5	38.90909091
0.535886731	50	40.47619048
0.5	52.5	42.02898551
0.466516496	47.5	0
0.435275282	50	0
0.406126198	50	0
0.378929142	50	0
0.353553391	52.5	0
0.329876978	52.5	0
0.307786103	52.5	0
0.287174589	52.5	0
0.267943366	52.5	0
0.25	52.5	0
0.233258248	52.5	0
0.217637641	52.5	0
0.203063099	52.5	0
0.189464571	52.5	0
0.176776695	52.5	0
0.164938489	52.5	0
0.153893052	52.5	0
0.143587294	52.5	0
0.133971683	52.5	0
0.125	52.5	0
0.116629124	52.5	0
0.10881882	52.5	0
0.10153155	52.5	0
0.094732285	52.5	0
0.088388348	52.5	0

While the sigma value was fixed to 5.66, the C parameter value was varied. Table 3.9 shows the result. Highest accuracy of 52.50% and F1-score of 52.47% were obtained when the C values were from 48.50 to 64.

Table 3.9: *Varying the C parameter Values (Valence – Subject 1)*

C	Accuracy (%)	F1 (%)
0.015625	50	48.84910486
0.017948412	50	48.84910486
0.020617311	50	48.84910486
0.023683071	50	48.84910486
0.027204705	50	48.84910486
0.03125	50	48.84910486
0.035896824	50	48.84910486
0.041234622	50	48.84910486
0.047366143	50	48.84910486
0.05440941	50	48.84910486
0.0625	50	48.84910486
0.071793647	50	48.84910486
0.082469244	50	48.84910486
0.094732285	50	48.84910486
0.10881882	50	48.84910486
0.125	50	48.84910486
0.143587294	50	48.84910486
0.164938489	47.5	46.66666667
0.189464571	47.5	46.66666667
0.217637641	47.5	47.20301697
0.25	47.5	47.20301697
0.287174589	47.5	47.20301697
0.329876978	47.5	47.46716698
0.378929142	47.5	47.46716698
0.435275282	47.5	47.46716698
0.5	47.5	47.46716698
0.574349177	47.5	47.46716698
0.659753955	47.5	47.46716698
0.757858283	47.5	47.46716698

0.870550563	47.5	47.46716698
1	47.5	47.46716698
1.148698355	47.5	47.46716698
1.319507911	47.5	47.20301697
1.515716567	45	44.86215539
1.741101127	45	44.86215539
2	45	44.86215539
2.29739671	45	44.86215539
2.639015822	45	44.86215539
3.031433133	45	44.86215539
3.482202253	45	44.86215539
4	45	44.86215539
4.59479342	45	44.86215539
5.278031643	45	44.86215539
6.062866266	42.5	42.46404003
6.964404506	40	40
8	40	39.84962406
9.18958684	42.5	42.46404003
10.55606329	47.5	47.46716698
12.12573253	47.5	47.46716698
13.92880901	47.5	47.46716698
16	47.5	47.46716698
18.37917368	45	45
21.11212657	47.5	47.46716698
24.25146506	50	49.87468672
27.85761803	50	49.87468672
32	50	49.87468672
36.75834736	50	49.87468672
42.22425314	50	49.87468672
48.50293013	52.5	52.47029393
55.71523605	52.5	52.47029393
64	52.5	52.47029393

The first participant's classification experiment with arousal targets are as follows. Table 3.10 shows the result obtained when the value for the 'rbf_sigma' is varied.

Highest accuracy of 55.00% and F1-score of 54.55% were obtained when the sigma value were 5.66 and 5.28.

Table 3.10: *Varying Sigma Values (Arousal – Subject 1)*

Sigma	Accuracy (%)	F1 (%)
5.656854249	55	54.54545455
5.278031643	55	54.54545455
4.924577653	52.5	51.74603175
4.59479342	50	49.49494949
4.28709385	50	49.49494949
4	50	49.49494949
3.732131966	50	49.49494949
3.482202253	45	44.44444444
3.249009585	45	44.44444444
3.031433133	42.5	41.58730159
2.828427125	42.5	41.58730159
2.639015822	37.5	36.50793651
2.462288827	37.5	36.50793651
2.29739671	32.5	31.42857143
2.143546925	32.5	31.42857143
2	30	28.3887468
1.866065983	25	21.875
1.741101127	27.5	23.63396972
1.624504793	27.5	23.63396972
1.515716567	37.5	30.11879804
1.414213562	37.5	30.11879804
1.319507911	40	31.62393162
1.231144413	40	31.62393162
1.148698355	42.5	33.09090909
1.071773463	42.5	33.09090909
1	42.5	0
0.933032992	45	0
0.870550563	45	0
0.812252396	52.5	0
0.757858283	52.5	0
0.707106781	57.5	0

0.659753955	57.5	0
0.615572207	60	0
0.574349177	60	0
0.535886731	60	0
0.5	60	0
0.466516496	60	0
0.435275282	60	0
0.406126198	60	0
0.378929142	60	0
0.353553391	60	0
0.329876978	60	0
0.307786103	60	0
0.287174589	60	0
0.267943366	60	0
0.25	60	0
0.233258248	60	0
0.217637641	60	0
0.203063099	60	0
0.189464571	60	0
0.176776695	60	0
0.164938489	60	0
0.153893052	60	0
0.143587294	60	0
0.133971683	60	0
0.125	60	0
0.116629124	60	0
0.10881882	60	0
0.10153155	60	0
0.094732285	60	0
0.088388348	60	0

While the sigma value was fixed to 5.66, the C parameter value was varied. Table 3.11 shows the result. Highest accuracy of 62.50% and F1-score of 61.32 % were obtained when the C value was 4.

Table 3.11: *Varying the C parameter Values (Arousal– Subject 1)*

C	Accuracy (%)	F1 (%)
0.015625	55	54.88721805
0.017948412	55	54.88721805
0.020617311	55	54.88721805
0.023683071	55	54.88721805
0.027204705	55	54.88721805
0.03125	55	54.88721805
0.035896824	55	54.88721805
0.041234622	55	54.88721805
0.047366143	55	54.88721805
0.05440941	55	54.88721805
0.0625	55	54.88721805
0.071793647	55	54.88721805
0.082469244	55	54.88721805
0.094732285	55	54.88721805
0.10881882	55	54.88721805
0.125	55	54.88721805
0.143587294	55	54.88721805
0.164938489	55	54.88721805
0.189464571	55	54.88721805
0.217637641	55	54.88721805
0.25	55	54.88721805
0.287174589	55	54.88721805
0.329876978	55	54.88721805
0.378929142	55	54.88721805
0.435275282	55	54.88721805
0.5	55	54.88721805
0.574349177	57.5	57.25958517
0.659753955	57.5	57.25958517
0.757858283	57.5	57.25958517
0.870550563	57.5	57.25958517
1	55	54.54545455
1.148698355	55	54.54545455
1.319507911	55	54.54545455
1.515716567	55	54.54545455
1.741101127	55	54.54545455

2	55	54.54545455
2.29739671	55	54.54545455
2.639015822	55	54.54545455
3.031433133	57.5	56.82539683
3.482202253	60	59.07928389
4	62.5	61.31528046
4.59479342	60	58.33333333
5.278031643	60	58.33333333
6.062866266	57.5	56.15731786
6.964404506	52.5	50.99935525
8	52.5	50.99935525
9.18958684	52.5	50.99935525
10.55606329	52.5	50.99935525
12.12573253	50	48.84910486
13.92880901	52.5	50.99935525
16	55	53.125
18.37917368	55	53.125
21.11212657	52.5	50.99935525
24.25146506	52.5	50.99935525
27.85761803	52.5	50.99935525
32	50	47.91666667
36.75834736	50	47.91666667
42.22425314	47.5	44.70046083
48.50293013	47.5	44.70046083
55.71523605	47.5	44.70046083
64	47.5	44.70046083

3.5 Chapter Summary

This chapter begins with an introduction to the general process of this study based on the objectives described. In general, there are three phases in this study. Each phase was explained in details in each section.

CHAPTER FOUR
RESULTS

4.1 Phase 1 Results: Algorithm for DWPT and Entropy

The algorithm developed for the DWPT decomposition and the computation of the entropy values is shown in Appendix A. Table 4.1 shows an excerpt of the resulting entropy values for theta, alpha, beta, and gamma bands for the channel Fp1 for all the 40 trials for subject number 1.

Table 4.1: *Entropy Values from Fp1 for Subject One's 40 Trials*

Trails\Bands	Theta	Alpha	Beta	Gamma
1	-158743	-80874.7	-192057	63.03318
2	-226961	-87087	-217525	75.5363
3	-209151	-124752	-230029	80.50354
4	-185340	-79206.7	-187446	52.59081
5	-102368	-56654.4	-163767	57.49537
6	-156800	-65281.1	-207134	62.82949
7	-205341	-73228.1	-218550	59.63153
8	-274076	-97631.4	-276030	74.26857
9	-278363	-124973	-289950	73.85778
10	-175410	-98796.6	-221039	64.98342
11	-240170	-85304.4	-205160	65.11224
12	-213020	-101826	-235760	67.84292
13	-213889	-87533.3	-254890	80.33206
14	-264273	-94044.3	-240405	5.117103
15	-171355	-88912.2	-208013	61.40405
16	-148961	-70221.7	-204000	58.89575
17	-138119	-52932.2	-188065	63.49298
18	-137799	-51037.1	-165200	63.42447
19	-161983	-80764.3	-216824	70.17283
20	-164501	-88691.5	-235361	63.17639
21	-209115	-99020.6	-226638	77.76733

22	-172445	-93545.5	-245166	75.46902
23	-157639	-88117.7	-265421	65.67862
24	-136875	-76230.6	-188224	59.17727
25	-212403	-113874	-258998	71.54993
26	-195431	-133798	-431927	95.56871
27	-200085	-106610	-318555	97.04297
28	-205439	-85642.4	-217711	70.34093
29	-133620	-61714.2	-178587	56.70762
30	-232339	-105272	-237404	62.9239
31	-104604	-66185.4	-186628	66.37853
32	-193456	-108189	-260407	58.45324
33	-198644	-123099	-212960	66.99817
34	-155266	-101787	-216636	67.78074
35	-134138	-75843.2	-218837	67.02626
36	-171054	-97333.4	-247476	80.13474
37	-251617	-99388.5	-254972	74.5467
38	-167527	-73044.8	-219663	59.96641
39	-145512	-70808.9	-207588	79.86364
40	-115712	-69017.1	-189667	66.89374

To cross check the values, One-Dimensional Discrete Wavelet Packet Analysis Tool from the MATLAB Wavelet Toolbox Main Menu was used to decompose the EEG signals and compute the entropy for Subject One's 40 trails. The result shows similar values of entropy with the MATLAB routine developed as illustrated in Figures 4.1 and Figure 4.2. Theta is located in 16, alpha in 17, low and high beta are located in 4 and 38, and gamma is located in 11 position of the decomposition tree. For the trial number 40 of the Fp1, the entropy value for the theta is -115712, entropy value for alpha is -69017, entropy value for beta is the addition of -120360 and -69308 which is -189668, and the entropy value for gamma is 66.8937. These values are same with the entropy values computed after implementing the DWPT decomposition shown in Table 4.1.

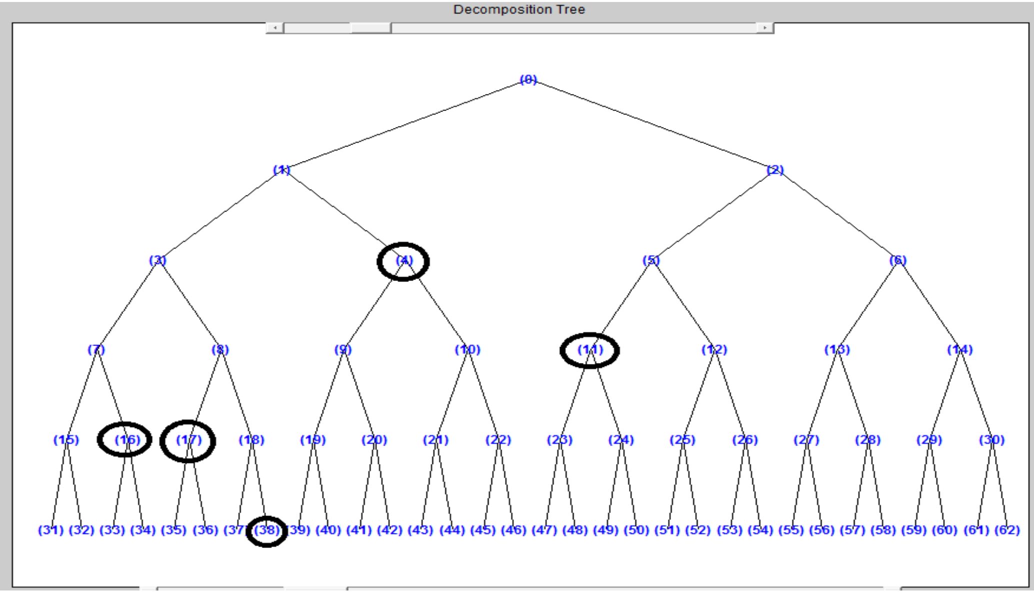


Figure 4.1. DWPT Decomposition Tree with Bands Index Numbers

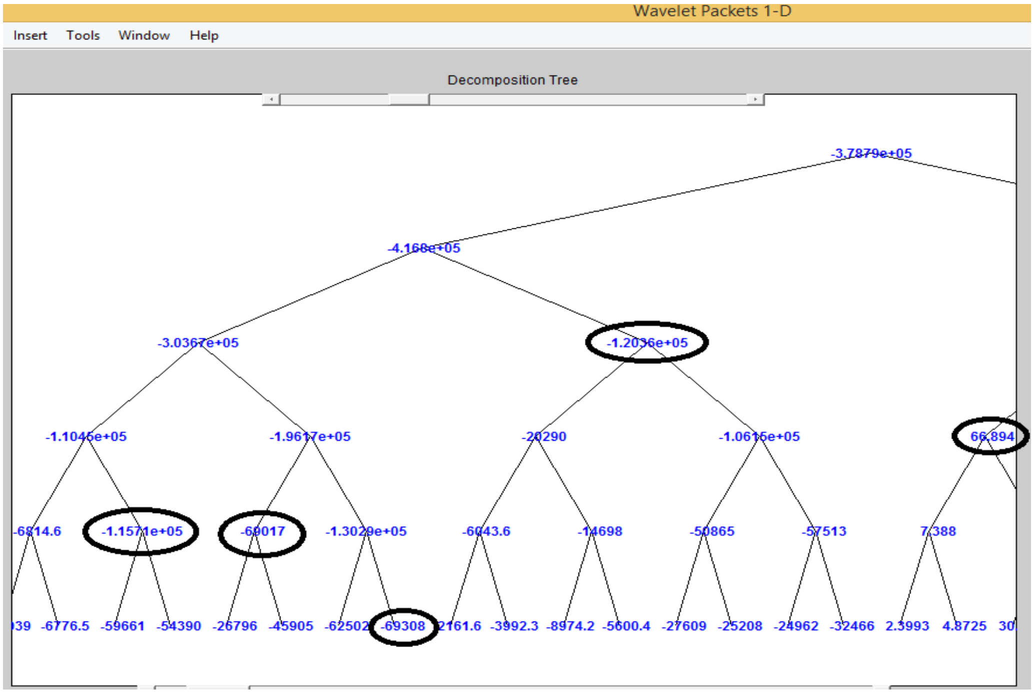


Figure 4.2. Theta, Alpha, Beta, and Gamma Entropy Values via Fp1 for Trial 40

4.2 Phase 2 Results

Two results are presented in this section. The average accuracy and F1-score obtained over the 32 subjects after the classification experiment using 10 channels are presented in section 4.2.1. The results when compared with Wichakam and Vateekul (2014) are as shown in section 4.2.2.

4.2.1 Average Accuracy and F1-Score for 10 Channels

The classification accuracy and F1-score values for all the 32 subjects are presented in Figure 4.3 and Figure 4.4 respectively. Averaged accuracy and F1-score over the 32 subjects is shown in Table 4.2. The average accuracy over all the 32 subjects for valence and arousal were 68.83% and 68.83% respectively. The average F1-score over all the 32 subjects for valence and arousal were 66.59% and 63.28% respectively.

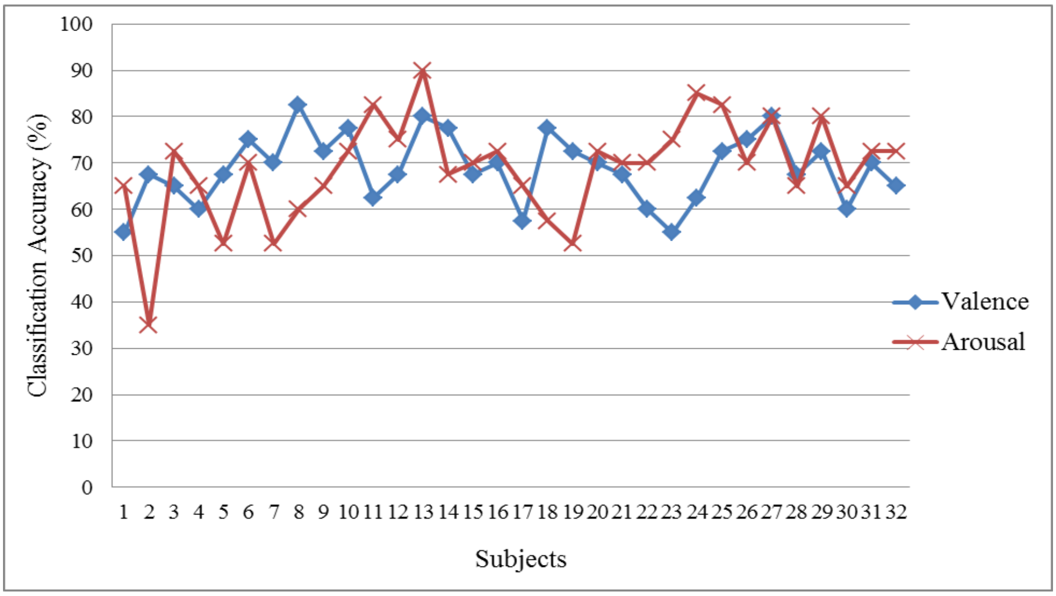


Figure 4.3. Classification Accuracy for 32 Subjects

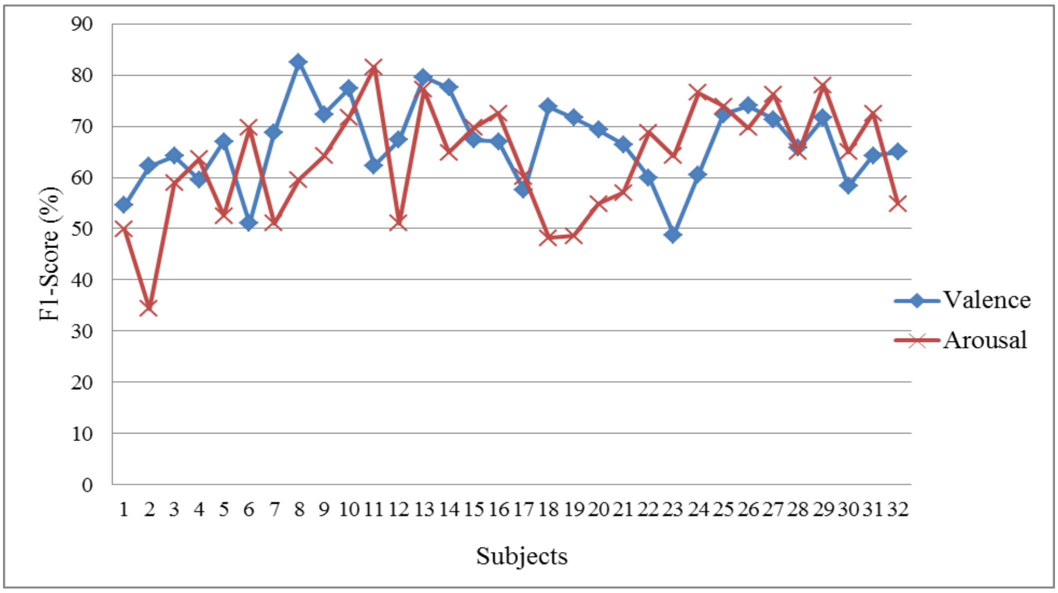


Figure 4.4. F1-Score for 32 Subjects

Table 4.2: *Phase 2 Classification Experiment Result for all 32 Subjects*

Subjects	Accuracy (%)		F1-Score (%)	
	Valence	**Arousal**	**Valence**	**Arousal**
1	55.00	65.00	54.55	49.82
2	67.50	35.00	62.18	34.34
3	65.00	72.50	64.19	58.92
4	60.00	65.00	59.60	63.54
5	67.50	52.50	66.98	52.47
6	75.00	70.00	50.98	69.70
7	70.00	52.50	68.75	51.00
8	82.50	60.00	82.49	59.60
9	72.50	65.00	72.34	64.19
10	77.50	72.50	77.37	71.63
11	62.50	82.50	62.29	81.57
12	67.50	75.00	67.32	50.98
13	80.00	90.00	79.54	77.14
14	77.50	67.50	77.49	64.84
15	67.50	70.00	67.32	69.70
16	70.00	72.50	67.03	72.48
17	57.50	65.00	57.47	60.11
18	77.50	57.50	73.82	48.13

19	72.50	52.50	71.63	48.61
20	70.00	72.50	69.31	54.87
21	67.50	70.00	66.47	56.99
22	60.00	70.00	60.00	68.75
23	55.00	75.00	48.72	64.16
24	62.50	85.00	60.50	76.56
25	72.50	82.50	72.34	73.86
26	75.00	70.00	73.96	69.70
27	80.00	80.00	71.33	76.19
28	67.50	65.00	65.77	64.91
29	72.50	80.00	71.63	78.02
30	60.00	65.00	58.33	64.91
31	70.00	72.50	64.29	72.48
32	65.00	72.50	64.91	54.88
Average	**68.83**	**68.83**	**66.59**	**63.28**

4.2.2 Results of DWPT Compared With Powerband

The classification results achieved in this work are higher compared to those obtained in Wichakam and Vateekul (2014) as shown in Table 4.3. The average accuracy value 0.688 achieved in this study for the valence classification is higher than 0.649 achieved in Wichakam and Vateekul (2014). The average accuracy value 0.688 achieved in this study for the arousal classification is also higher than 0.649 achieved in Wichakam and Vateekul (2014). The average F1-score value 0.666 achieved in this study for the valence classification is higher than 0.514 achieved in Wichakam and Vateekul (2014). The average F1-score value 0.633 achieved in this study for the arousal classification is also higher than 0.508 achieved in Wichakam and Vateekul (2014). These results are compared in Figure 4.5 and Figure 4.6.

Table 4.3: *The Result of DWPT Compared With Powerband*

Author /Year	Electrode Channels	Features/ Feature Extraction Method	Classifier	Accuracy		F1-Score	
				V	A	V	A
Current Study	Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2.	theta, alpha, beta and gamma, entropy features using DWPT	RBF-SVM	**0.688**	**0.688**	**0.666**	**0.633**
Wichakam & Vateekul, 2014	Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2.	theta, alpha, beta and gamma, band-power features	RBF-SVM	0.649	0.649	0.514	0.508

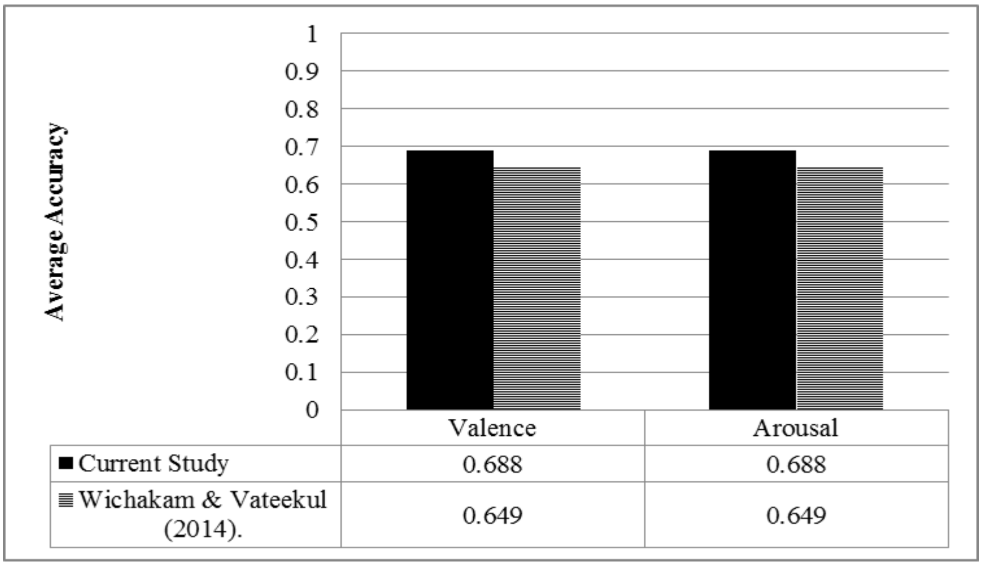


Figure 4.5. Average Accuracy Compared

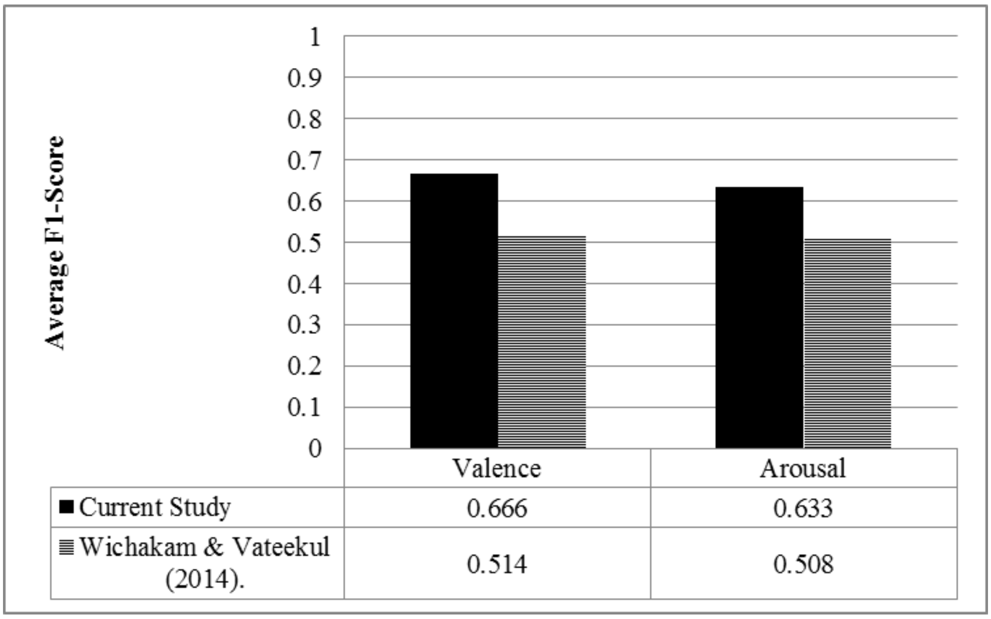


Figure 4.6. Average F1-Score Compared

In summary, the results achieved in this study using DWPT to extract entropy features are higher compared to that achieved in Wichakam and Vateekul (2014) using bandpower features. This shows that entropy features by DWPT are better than bandpower features for EEG-based valence-arousal emotion recognition.

4.3 Phase 3 Results

Two results are presented in this section. The average accuracy and F1-score obtained over the 32 subjects after the classification experiment using 4 channels are presented in section 4.3.1. The results when compared with that of 10 channels are as shown in section 4.3.2.

4.3.1 Average Accuracy and F1-Score for 4 Channels

The classification accuracy and F1-score values for all the 32 subjects are presented in Figure 4.7 and Figure 4.8 respectively. The accuracy and F1-score for all the 32 subjects were averaged. Table 4.4 shows the accuracy and F1-scores values and the average for both the valence and arousal classification experiments. The average accuracy over all the 32 subjects for valence and arousal was 69.45% and 67.27% respectively. The average F1-score over all the 32 subjects for valence and arousal were 67.67% and 61.32% respectively.

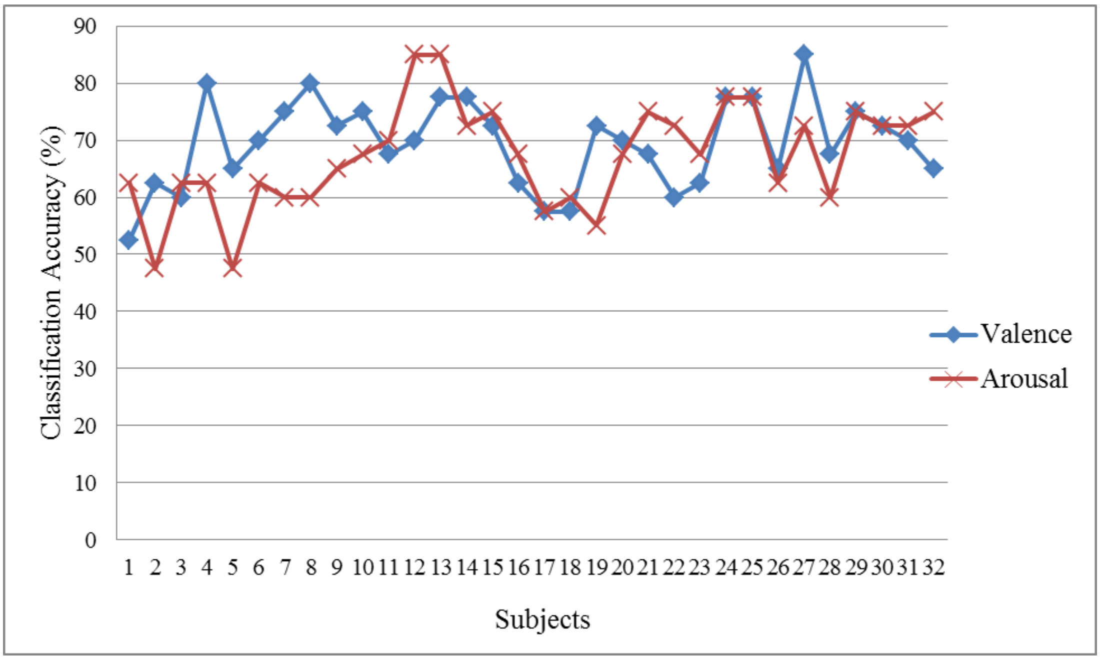


Figure 4.7. Classification Accuracy for 32 Subjects

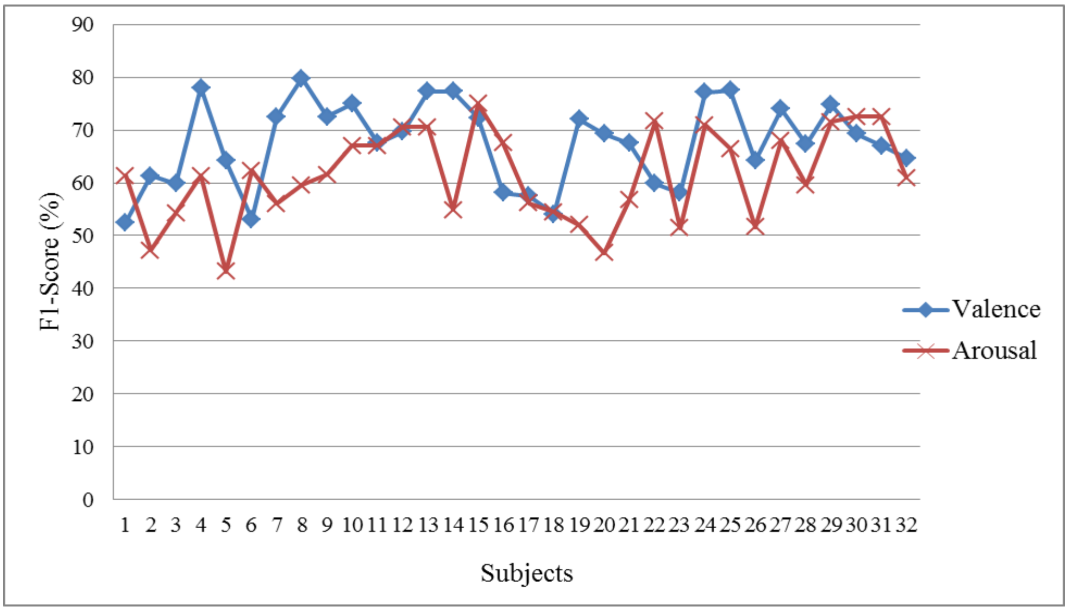


Figure 4.8. F1-Score for 32 Subjects

Table 4.4: *Phase 3 Classification Experiment Result for all 32 Subjects*

Subjects	Accuracy (%)		F1 Score (%)	
	Valence	Arousal	Valence	Arousal
1	52.50	62.50	52.47	61.32
2	62.50	47.50	61.32	47.20
3	60.00	62.50	59.90	54.23
4	80.00	62.50	78.02	61.32
5	65.00	47.50	64.19	43.20
6	70.00	62.50	53.13	62.29
7	75.00	60.00	72.53	56.04
8	80.00	60.00	79.80	59.60
9	72.50	65.00	72.48	61.54
10	75.00	67.50	75.00	66.98
11	67.50	70.00	67.48	67.03
12	70.00	85.00	69.70	70.59
13	77.50	85.00	77.37	70.59
14	77.50	72.50	77.37	54.87
15	72.50	75.00	72.34	74.94
16	62.50	67.50	58.07	67.48
17	57.50	57.50	57.47	56.16

18	57.50	60.00	54.03	54.42
19	72.50	55.00	72.06	52.00
20	70.00	67.50	69.31	46.67
21	67.50	75.00	67.48	56.71
22	60.00	72.50	59.90	71.63
23	62.50	67.50	58.07	51.45
24	77.50	77.50	77.14	70.94
25	77.50	77.50	77.49	66.39
26	65.00	62.50	64.19	51.57
27	85.00	72.50	74.03	68.00
28	67.50	60.00	67.32	59.60
29	75.00	75.00	74.75	71.51
30	72.50	72.50	69.25	72.48
31	70.00	72.50	67.03	72.48
32	65.00	75.00	64.65	60.94
Average	**69.45**	**67.27**	**67.67**	**61.32**

4.3.2 Results of 4 Channels Compared With 10 Channels

The results obtained using the 4 channels Fp1, Fp2, F3, and F4 compared with the results obtained using the 10 channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 are presented in Table 4.5.

Table 4.5: *The Results of 4 Channels Compared with 10 Channels*

No. of Channels	**Electrode Channels**	**Accuracy**		**F1-Score**	
		V	**A**	**V**	**A**
10 Channels	Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2.	0.688	**0.688**	0.666	**0.633**
4 Channels	Fp1, Fp2, F3, and F4	**0.695**	0.673	**0.677**	0.613

The average accuracy value 0.695 achieved for the valence classification using 4 channels is higher than 0.688 using 10 channels. Also the average F1-score value 0.677 achieved for the valence classification using 4 channels is higher than 0.666 using 10 channels. The average accuracy value 0.688 achieved for the arousal classification using 10 channels is higher than 0.673 using 4 channels. Also the average F1-score value 0.633 achieved for the arousal classification using 10 channels is higher than 0.613 using 4 channels.

The results shows that average accuracy and F1-score values obtained while using the 4 channels were higher than the 10 channels for valence level emotions recognition. On the other hand, average accuracy and F1-score values obtained while using the 10 channels were higher than the 4 channels for arousal level emotions recognition. As shown in Figure 4.9 and Figure 4.10.

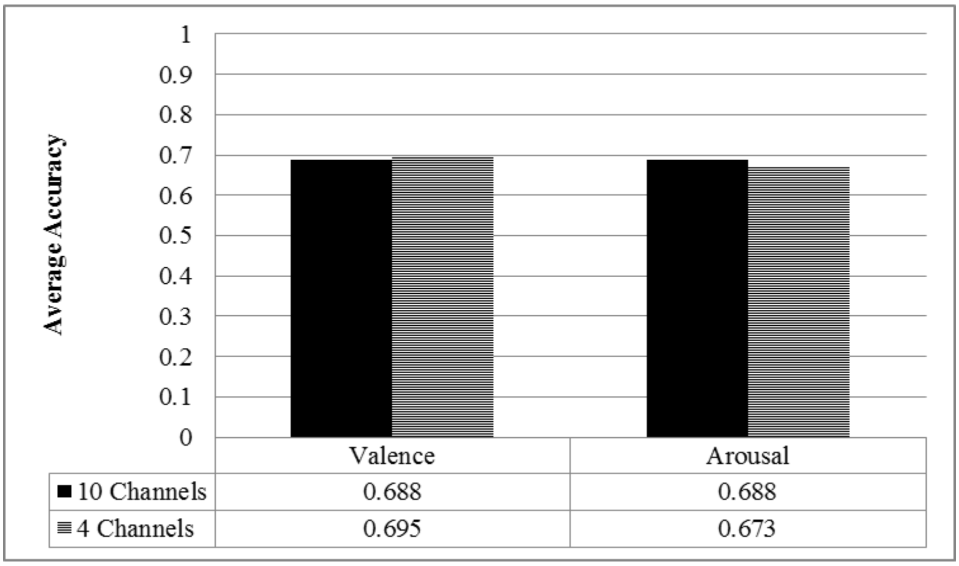


Figure 4.9. Average Accuracy of 4 Channels Compared with 10 Channels

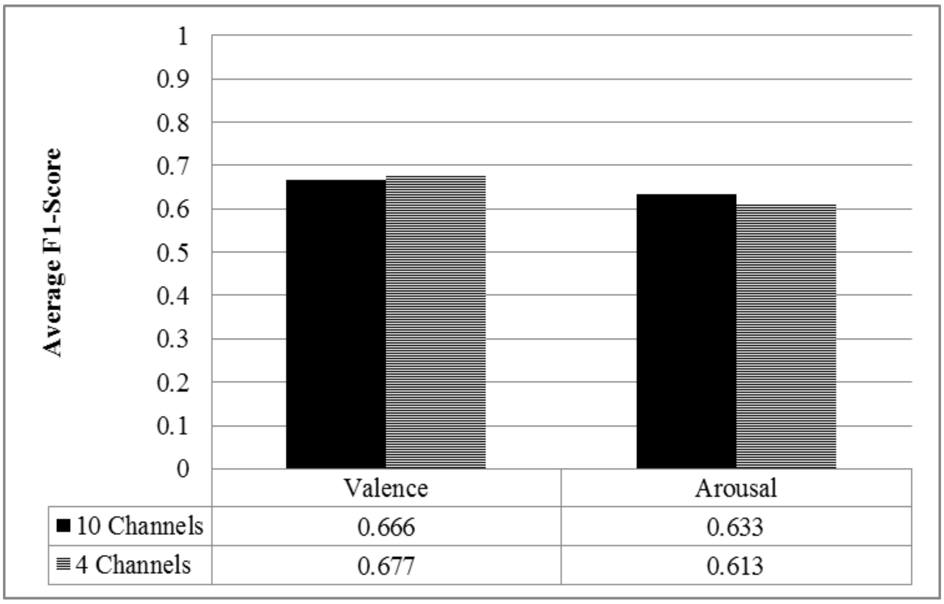


Figure 4.10. Average F1-Score of 4 Channels Compared with 10 Channels

4.4 Chapter Summary

In this chapter, the results obtained after using DWPT to extract entropy features were presented. The classification results for each of the experiments performed were presented and the results were compared.

CHAPTER FIVE
CONCLUSION

Based on the main objective of this study, that is to discover the feature extraction method and the combination of electrode channels that optimally implements EEG-based valence-arousal emotion recognition, DWPT was proposed as a feature extraction method and two emotion recognition experiments were performed to classify human emotional states into high/low valence or high/low arousal.

The first experiment was aimed at comparing the results of the study carried out by Wichakam and Vateekul (2014) using bandpower features to the result achieved in this study using DWPT to extract entropy features. The entropy features of the theta, alpha, beta, and gamma bands through 10 EEG channels Fp1, Fp2, F3, F4, T7, T8, P3, P4, O1, and O2 were extracted using DWPT and RBF-SVM was used as the classifier. The result of this experiment showed that entropy features extracted using DWPT are better than the bandpower features. Moreover it has previously been showed in Wichakam and Vateekul (2014) that bandpower method is better than the PSD by wavelet transform method. So it can be concluded that entropy by DWPT is better than bandpower and subsequently better than the PSD by wavelet transform method.

The second experiment was aimed at comparing the result achieved in the first experiment using the 10 channels with another combination of 4 channels Fp1, Fp2, F3, and F4 in order to identify the combination of electrode channels that optimally recognize emotions based on the valence-arousal model in EEG emotion recognition.

The result of the second classification experiment shows that the combination of the 4 channels gives higher accuracy than the combination the 10 channels for only valence level emotion recognition. On the other hand, the combination of the 10 channels gives higher accuracy than the 4 channels for only arousal level emotions recognition. This result indicated that the combination of the 4 frontal channels Fp1, Fp2, F3, and, F4 are significant for EEG-based emotion recognition in the valence-arousal space and the addition of the remaining 6 channels T7, T8, P3, P4, O1, and O2 are not essential. Moreover, it has previously been identified by Wichakam and Vateekul (2014) that 10 channels give higher accuracy than 32 channels. So it can be concluded that the combination of the 4 channels are better than the combination of the 10 channels and subsequently better than the combination of the 32 channels.

This finding is in line with other previous studies that have proved that human emotions can be recognized by acquiring brain signals from the frontal region of the brain (Coan and Allen, 2004; Davidson, 2004) and specifically these 4 frontal channels (Bastos-Filho, Ferreira, Atencio, Arjunan, and Kumar, 2012; Singh, Jati, Khasnobish, Bhattacharyya, Konar, Tibarewala, and Janarthanan, 2012; Petrantonakis and Hadjileontiadis, 2010).

Future works should be focused on implementing these combinations of channels and feature extraction method on another dataset in order to validate the result and findings in this work. Further effort should be made to utilize these findings to build systems that are specific in solving real life medical problems.

REFERENCES

Aftanas, L. I., Reva, N. V., Varlamov, A. A., Pavlov, S. V., & Makhnev, V. P. (2004). Analysis of evoked EEG synchronization and desynchronization in conditions of emotional activation in humans: temporal and topographic characteristics. *Neuroscience and behavioral physiology*, *34*(8), 859-867.

AlZoubi, O., Calvo, R. A., & Stevens, R. H. (2009). Classification of EEG for affect recognition: an adaptive approach. In *AI 2009: Advances in Artificial Intelligence* (pp. 52-61). Springer Berlin Heidelberg

Amaral, V., Ferreira, L. A., Aquino, P. T., & de Castro, M. C. F. (2013). EEG signal classification in usability experiments. In Biosignals and Biorobotics Conference (BRC), 2013 ISSNIP (pp. 1-5). IEEE.

Bahari, F., & Janghorbani, A. (2013). EEG-based emotion recognition using Recurrence Plot analysis and K nearest neighbor classifier. In Biomedical Engineering (ICBME), 2013 20th Iranian Conference on (pp. 228-233). IEEE.

Bastos-Filho, T. F., Ferreira, A., Atencio, A. C., Arjunan, S., & Kumar, D. (2012, December). Evaluation of feature extraction techniques in emotional state recognition. In Intelligent Human Computer Interaction (IHCI), 2012 4th International Conference on (pp. 1-6). IEEE.

Bos, D. O. (2007). EEG-based Emotion Recognition: The Influence of Visual and Auditory Stimuli. Capita Selecta Paper. Retrieved from http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:EEG-based+Emotion+Recognition+The+Influence+of+Visual+and+Auditory+Stimuli#2

Cabredo, R., Legaspi, R. S., Inventado, P. S., & Numao, M. (2013). Discovering Emotion-Inducing Music Features Using EEG Signals. JACIII, 17(3), 362-370.)

Chanel, G., Kronegg, J., Grandjean, D., & Pun, T. (2006). Emotion assessment: Arousal evaluation using EEG’s and peripheral physiological signals. In Multimedia content representation, classification and security (pp. 530-537). Springer Berlin Heidelberg.

Chanel, G. (2009). Emotion assessment for affective computing based on brain and peripheral signals (Doctoral dissertation, University of Geneva).

Coan, J. A., & Allen, J. J. (2004). Frontal EEG asymmetry as a moderator and mediator of emotion. *Biological psychology, 67*(1), 7-50.

Dauwels, J., & Vialatte, F. (2010). Topics in Brain Signal Processing. Nanyang Technological University, Singapore (IEEE J-STSP), ISSN1941-0484.

Davidson, R. J. (2004). What does the prefrontal cortex “do” in affect: perspectives on frontal EEG asymmetry research. *Biological psychology*,*67*(1), 219-234.

Dayan, P., & Abbott, L. (2000). Theoretical neuroscience: computational and mathematical modeling of neural systems. Retrieved from http://cns-classes.bu.edu/cn510/Papers/Theoretical Neuroscience Computational and Mathematical Modeling of Neural Systems - Peter Dayan, L. F. Abbott.pdf

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of neuroscience methods, 134(1), 9-21.

Fu, S. Y., Yang, G. S., & Hou, Z. G. (2011, July). Spiking neural networks based cortex like mechanism: a case study for facial expression recognition. In Neural Networks (IJCNN), The 2011 International Joint Conference on (pp. 1637-1642). IEEE.

Garcia–Molina, G., Tsoneva, T., & Nijholt, A. (2013). Emotional brain–computer interfaces. International Journal of Autonomous and Adaptive Communications Systems, 6(1), 9-25.

Gráfová, L., Vyšata, O., & Procházka, A. (2010). Feature Analysis of EEG Signals Using SOM. Institute of Chemical Technology Department of Computing and Control Engineering, Technicka. Retrieved from http://dsp.vscht.cz/konference_matlab/MATLAB10/full_text/031_Grafova.pdf

Hosseini, S. A., & Khalilzadeh, M. A. (2010, April). Emotional stress recognition system using EEG and psychophysiological signals: Using new labelling process of EEG signals in emotional stress state. In Biomedical Engineering and Computer Science (ICBECS), 2010 International Conference on (pp. 1-6). IEEE.

Hosseini, S., & Naghibi-Sistani, M. (2009). Classification of Emotional Stress Using Brain Activity. Retrieved from http://cdn.intechweb.org/pdfs/18027.pdf

Hosseini, S. A. (2012). Classification of Brain Activity in Emotional States Using HOS Analysis. International Journal of Image, Graphics and Signal Processing (IJIGSP), 4(1), 21.

Hwang, H. J., Kim, S., Choi, S., & Im, C. H. (2013). EEG-Based Brain-Computer Interfaces: A Thorough Literature Survey. International Journal of Human-Computer Interaction, 29(12), 814-826.

Jahankhani, P., Kodogiannis, V., & Revett, K. (2006, October). EEG signal classification using wavelet feature extraction and neural networks. In Modern Computing, 2006. JVA'06. IEEE John Vincent Atanasoff 2006 International Symposium on (pp. 120-124). IEEE.

Jatupaiboon, N., Pan-ngum, S., & Israsena, P. (2013, a). Emotion classification using minimal EEG channels and frequency bands. In Computer Science and Software Engineering (JCSSE), 2013 10th International Joint Conference on (pp. 21-24). IEEE.

Jatupaiboon, N., Pan-ngum, S., & Israsena, P. (2013,b). Real-time EEG-based happiness detection system. The Scientific World Journal, 2013.

Jie, X., Cao, R., & Li, L. (2014). Emotion recognition based on the sample entropy of EEG. Bio-medical materials and engineering, 24(1), 1185-1192.

Kensinger, E. A. (2004). Remembering emotional experiences: The contribution of valence and arousal. Reviews in the Neurosciences, 15(4), 241-252.

Khalili, Z., & Moradi, M. H. (2009). Emotion recognition system using brain and peripheral signals: using correlation dimension to improve the results of EEG. In *Neural Networks, 2009. IJCNN 2009. International Joint Conference on* (pp. 1571-1575). IEEE.

Kim, J., & André, E. (2006). Emotion recognition using physiological and speech signal in short-term observation. In Perception and interactive technologies (pp. 53-64). Springer Berlin Heidelberg.

Kim, J., & André, E. (2008). Emotion recognition based on physiological changes in music listening. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 30(12), 2067-2083.

Kim, K. H., Bang, S. W., & Kim, S. R. (2004). Emotion recognition system using short-term monitoring of physiological signals. Medical and biological engineering and computing, 42(3), 419-427.

Kiymik, M. K., Akin, M., & Subasi, A. (2004). Automatic recognition of alertness level by using wavelet transform and artificial neural network. Journal of neuroscience methods, 139(2), 231-240.

Koelstra, S., Muhl, C., Soleymani, M., Lee, J. S., Yazdani, A., Ebrahimi, T., ... & Patras, I. (2012). Deap: A database for emotion analysis; using physiological signals. Affective Computing, IEEE Transactions on, 3(1), 18-31.

Kwon, M., Ahn, M., Hong, J. H., Park, S., Park, T., & Jun, S. C. (2013, November). Valence detection for image stimulated EEG data. In Neural Engineering (NER), 2013 6th International IEEE/EMBS Conference on (pp. 109-112). IEEE.

Li, M., & Lu, B. L. (2009). Emotion classification based on gamma-band EEG. In Engineering in Med-icine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE (pp. 1223-1226). IEEE.

Lin, Y. P., Wang, C. H., Jung, T. P., Wu, T. L., Jeng, S. K., Duann, J. R., & Chen, J. H. (2010). EEG-based emotion recognition in music listening. Biomedical Engineering, IEEE Transactions on, 57(7), 1798-1806.

Liu, Y., Sourina, O., & Nguyen, M. K. (2011). Real-time EEG-based emotion recognition and its applications. In Transactions on computational science XII(pp. 256-277). Springer Berlin Heidelberg.

Mathieu, N. G., Bonnet, S., Harquel, S., Gentaz, E., & Campagne, A. (2013, November). Single-trial ERP classification of emotional processing. In Neural Engineering (NER), 2013 6th International IEEE/EMBS Conference on (pp. 101-104). IEEE.

Mauss, I. B., & Robinson, M. D. (2009). Measures of emotion: A review. Cognition and emotion, 23(2), 209-237.

Mazaeva, N., Ntuen, C., & Lebby, G. (2001, July). Self-Organizing Map (SOM) model for mental workload classification. In IFSA World Congress and 20th NAFIPS International Conference, 2001. Joint 9th (Vol. 3, pp. 1822-1825). IEEE.

Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Hazry, D., & Zunaidi, I. (2008, January). Time-frequency analysis of EEG signals for human emotion detection. In 4th Kuala Lumpur International Conference on Biomedical Engineering 2008 (pp. 262-265). Springer Berlin Heidelberg.

Murugappan, M., Rizon, M., Nagarajan, R., Yaacob, S., Zunaidi, I., & Hazry, D. (2008, August). Lifting scheme for human emotion recognition using EEG. In Information Technology, 2008. ITSim 2008. International Symposium on (Vol. 2, pp. 1-7). IEEE.

Murugappan, M., Rizon, M., Nagarajan, R., & Yaacob, S. (2009). FCM clustering of Human Emotions using Wavelet based Features from EEG. The official Journal of the Biomedical Fuzzy Systems Association, 35.

Murugappan, M., Ramachandran, N., & Sazali, Y. (2010). Classification of human emotion from EEG using discrete wavelet transform. Journal of Biomedical Science and Engineering, 03(04), 390–396. doi:10.4236/jbise.2010.34054

Murugappan, M., Nagarajan, R., & Yaacob, S. (2011). Combining spatial filtering and wavelet transform for classifying human emotions using EEG Signals. Journal of Medical and Biological Engineering, 31(1), 45-51.

Murugappan, M., Wali, M. K., Ahmmad, R. B., & Murugappan, S. (2013). Subtractive fuzzy classifier based driver drowsiness levels classification using EEG. In Communications and Signal Pro-cessing (ICCSP), 2013 International Conference on (pp. 159-164). IEEE.

Naser, D. S., & Saha, G. (2013). Recognition of emotions induced by music videos using DT-CWPT. In Medical Informatics and Telemedicine (ICMIT), 2013 Indian Conference on (pp. 53-57). IEEE.

Pei, M., Goodman, E. D., Punch, W. F., & Ding, Y. (1995, June). Genetic algorithms for classification and feature extraction. In Classification Society Conference.

Peterson, D. A., Knight, J. N., Kirby, M. J., Anderson, C. W., & Thaut, M. H. (2005). Feature selection and blind source separation in an EEG-based brain-computer interface. EURASIP Journal on Advances in Signal Processing, 2005(19), 3128-3140.

Petrantonakis, P. C., & Hadjileontiadis, L. J. (2010). Emotion recognition from EEG using higher order crossings. Information Technology in Biomedicine, IEEE Transactions on, 14(2), 186-197.

Picard, R. W., Vyzas, E., & Healey, J. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. Pattern Analysis and Machine Intelligence, IEEE Transactions on, 23(10), 1175-1191.

Posner, J., Russell, J. A., & Peterson, B. S. (2005). The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. Development and psychopathology, 17(03), 715-734.

Rached, T. S., & Perkusich, A. (2013). Emotion Recognition Based on Brain-Computer Interface Systems. Retrieved from http://cdn.intechopen.com/pdfs/44926/InTech-Emotion_recognition_based_on_brain_computer_interface_systems.pdf

Raymer, M. L., Punch, W. F., Goodman, E. D., Sanschagrin, P. C., & Kuhn, L. A. (1997, July). Simultaneous feature extraction and selection using a masking genetic algorithm. In Proceedings of the 7th International Conference on Genetic Algorithms, San Francisco, CA (pp. 561-567).

Riera Sardà, A. (2012). Computational Intelligence Techniques for Electro-Physiological Data Analysis. Retrieved from http://www.tesisenred.net/handle/10803/107818

Rozgic, V., Vitaladevuni, S. N., & Prasad, R. (2013). Robust EEG emotion classification using segment level decision fusion. In Acoustics, Speech and Signal Processing (ICASSP), 2013 IEEE International Conference on (pp. 1286-1290). IEEE.

Russell, J. A. (1980). A circumplex model of affect. Journal of personality and social psychology, 39(6), 1161.

Sanei, S., & Chambers, J. A. (2008). EEG signal processing. John Wiley & Sons. Retrieved from http://medcontent.metapress.com/index/A65RM03P4874243N.pdf

Singh, G., Jati, A., Khasnobish, A., Bhattacharyya, S., Konar, A., Tibarewala, D. N., & Janarthanan, R. (2012, July). Negative emotion recognition from stimulated EEG signals. In Computing Communication & Networking

Technologies (ICCCNT), 2012 Third International Conference on (pp. 1-8). IEEE.

Stickel, C., Ebner, M., Steinbach-Nordmann, S., Searle, G., & Holzinger, A. (2009). Emotion detection: application of the valence arousal space for rapid biological usability testing to enhance universal access. In Universal Access in Human-Computer Interaction. Addressing Diversity (pp. 615-624). Springer Berlin Heidelberg.

Scherer, K. R. (2005). What are emotions? And how can they be measured? Social Science Information, 44(4), 695–729. doi:10.1177/0539018405058216

Tsai, P. Y., Hu, W., Kuo, T. B., & Shyu, L. Y. (2009). A portable device for real time drowsiness detection using novel active dry electrode system. In Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE (pp. 3775-3778). IEEE.

Torres, C. A., Orozco, A. A., & Alvarez, M. A. (2013, July). Feature selection for multimodal emotion recognition in the arousal-valence space. In Engineering in Medicine and Biology Society (EMBC), 2013 35th Annual International Conference of the IEEE (pp. 4330-4333). IEEE.

Wang, X. W., Nie, D., & Lu, B. L. (2011, January). EEG-based emotion recognition using frequency domain features and support vector machines. In Neural Information Processing (pp. 734-743). Springer Berlin Heidelberg.

Wali, M. K., Murugappan, M., & Ahmmad, B. (2013). Wavelet packet transform based driver distrac-tion level classification using EEG. Mathematical Problems in Engineering, 2013.

Yang, J., Singh, H., Hines, E. L., Schlaghecken, F., Iliescu, D. D., Leeson, M. S., & Stocks, N. G. (2012). Channel selection and classification of electroencephalogram signals: An artificial neural network and genetic algorithm-based approach. Artificial intelligence in medicine, 55(2), 117-126.

Wichakam, I., & Vateekul, P. (2014). An evaluation of feature extraction in EEG-based emotion pre-diction with support vector machines. In Computer Science and Software Engineering (JCSSE), 2014 11th International Joint Conference on (pp. 106-110). IEEE.

Youn, Y., Jeon, H., Jung, H., & Lee, H. (2007). Discrete wavelet packet transform based energy detec-tor for cognitive radios. In Vehicular Technology Conference, 2007. VTC2007-Spring. IEEE 65th (pp. 2641-2645). IEEE.

Yuen, C. T., San, W. S., Seong, T. C., & Rizon, M. (2011). Classification of human emotions from EEG signals using statistical features and neural network. International Journal of Integrated Engineering, 1(3).

Zhuang, X., Rozgic, V., & Crystal, M. (2014). Compact unsupervised EEG response representation for emotion recognition. In Biomedical and Health Informatics (BHI), 2014 IEEE-EMBS International Conference on (pp. 736-739). IEEE.