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An Emotional BCI during Listening to Quran

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A thesis submitted for the requirements of the degree

of Master of Science in Computer Science

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This thesis has been approved and accepted in partial fulfillment of the requirements for the degree of Master of Science in Computer Science

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Dedicated to

To my beloved parents and my husband who taught me to be ambitious

To my kids who have endured my preoccupation about them

To all who supported me to complete this work

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An Emotional BCI during Listening to Quran

Mashail Laffai Alsolamy

Abstract

Brain Computer Interface (BCI) allows users to interact with external devices using their brainwave signals. On the other hand, emotions play an important role in our daily life and affect our decisions. To understanding better the behavior of the human being, his/her emotion should be estimated.

Different methods were proposed to estimate the subject's emotion. Most of these methods are based on subject's voice, face and body gestures which are not reliable because people can conceal their feelings. To overcome this problem, this work proposed a system to estimate the subject's emotion from his/her brainwaves that are reliable and enable us to know the inner emotions. To this end, an experiment was designed to make the user listening to Quran verses while the brainwaves are recorded and analyzed to estimate the subject's emotion.

The proposed model was applied and tested to 14 participants. The obtained results show that the proposed model correctly estimates the participant's emotions by accuracy 89.04%. More experiments are needed to evaluate the performance of the proposed model in real time.

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List of Symbols and Terminology

BCI	Brain Computer Interface
BMI	Brain Machine Interface
EEG	Electroencephalogram
FD	Fractal Dimension
FFT	Fast Fourier Transform
FMRI	Functional Magnetic Resonance Imaging
MEG	Magnetoencephalography
PET	Positron Emission Tomography
PSD	Power Spectral Density
WT	Wavelet Transform
SVM	Support Vector Machine
RF	Random Forest
RBF	Radial Basic Function

Chapter 1

Introduction

1.1 Background

Emotions play an important role in our thinking and behavior. Emotion recognition has many applications in different domains such as education [1], heath [2], commerce [3], and games [4]. However, the most important application for the computer scientists could be the natural language processing domain where the machine can understand the user's emotion and react upon this understanding [5].

Brain-Computer Interfaces (BCIs) provide direct communication between the brain activities and the computer [6]. BCIs are based on detecting and classifying specific patterns activities among brain signals that are associated with specific task or event [7]. Recent studies have been used brain signals to detect and classify the emotional state of the user because it is reliable.

According to the Islamic faith, Quran is the speech of Allah, revealed to Prophet Muhammad. It is argued that listening to it is an act of prayer which relaxes the heart and renews vitality of the body. Since the Holy Quran could influence on our mood and affect our health, this thesis aims to develop an emotionally-based BCI system where the emotional state of the user during listening to Quran can be detected and classified according to his brain signals.

1.2 Research Objectives

The goal of this research is to develop an emotional based BCI system during listening to Quran.

Accordingly, to achieve our goal, the objectives of this study would be:

1. Understanding in detail the emotional indicators.

2. Developing a model based on emotional indicators to classify the emotional state of the user during listening to Quran verses.

4. Testing that model to evaluate the effectiveness of it.

5. Implement a prototype as a proofing the concept.

1.3 Thesis Organization

The rest of this thesis is organized into six chapters as follows. **Chapters 2 and 3** contain background material and literature review; **Chapter 2** presents an introduction to Brain Computer Interface while **Chapter 3** dedicates to emotion recognition in BCI.

Chapters 4 and 5 mainly describe the core of this thesis; **Chapter 4** describes the methodology of this work while **Chapter 5** presents and discusses the results of applying the proposed model. **Chapter 6** presents the developing BCI system. **Chapter 7** gives a conclusion and an outlook on future work.

Chapter 2

Introduction to Brain Computer Interfaces (BCIs)

2.1 Introduction

In the case of disability, voluntary control of muscles is lost, the person is cognitively intact but cannot move his arms, face, or legs; this means all the kinetic commands confined inside his body. The only efficient way to communicate with the environment using a device that can read his brain signals and transform them into control and communication signals. This device is called a brain-computer interface (BCI) or a brain-machine interface (BMI), sometimes it is called a direct neural interface.

Controlling devices by brain signals were considered pure science imagination in the 60s. But in 1929, recording brain signals from the human scalp gained some attention when Hans Berger, a German neurologist, recorded the first electrical brain activity from the human scalp [8]. However, the technologies for measuring and processing those signals were too limited and also the understanding of brain function. Those limitations faded nowadays as neuroscience research over the last decades led to a better understanding of the brain and its activity. The computing power and signal processing algorithms have evolved so rapidly that became processing of brain signals in real-time does not need expensive or big equipment. Since then, a continuous stream of studies has triggered a massive interest in BCIs.

This interest stems from the great potential of this technology to recover of motor behaviors in severely physically challenged patients.

2.2 What is BCI?

Any control or communication requires muscles and peripheral nerves. The process starts with the intention of the user. This intention activates certain areas of the brain in which excites a complex process, and then corresponding muscles will receive signals by the peripheral nervous. This muscles, in turn, execute the movement necessary for the control or communication task. The output activity from this process is often called effort output or motor output. Effort means transfer impulses from central to a peripheral nervous system and then to muscle. In contrast, affort describes communication from the sensory receptors to the central nervous system. For movement control, the motor (efferent) pathway is fundamental. The sensory (afferent) pathway is especially important for learning motor skills and skillful tasks, such as typing or playing a musical instrument.

A BCI offers a substitute for natural communication and control. It is an artificial system that exceeds the normal paths issued in the body, which is neuromuscular output channels [9].

Instead of depending on muscles and peripheral nerves, a BCI directly measures brain activity associated with the user’s intent and translates the recorded brain activity into corresponding control signals for BCI applications. This translation includes signal processing and pattern recognition, which is typically done by a computer. Since the measured activity originates directly from the brain and not from the peripheral systems or muscles, the system is called a Brain–Computer Interface.

Therefore, the BCI is a direct communication pathway between the brain and an external device. It is often aimed at assisting, augmenting or repairing cognitive or sensory-motor functions of the human. It must have four components which are: recording activity directly from the brain, providing feedback to the user, and must do so in real time. Finally, the system must rely on intentional control via the user must choose to perform a psychical task to achieve a goal of the BCI. Devices that only passively detect changes in brain activity that occur without any intent, such as EEG activity associated with workload, arousal, or sleep, are not BCIs. Figure 2.1 illustrates the high-level block diagram of a general BCI system.

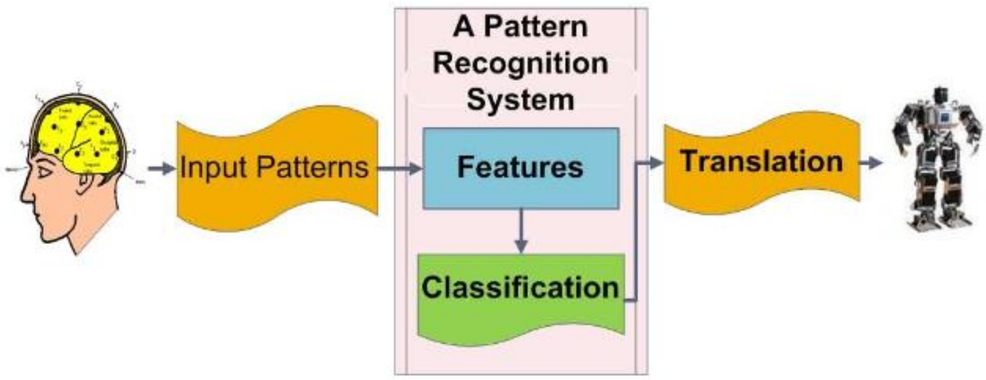


Figure 2.1 Basic BCI components [10].

The recording methods in BCI can be divided into two categories: invasive and non-invasive. The invasive methods are the insertion of electrodes below the skull, often onto the surface of the brain [11], but occasionally deep within the cortex for purposes of monitoring one particular region; this means the user undergoes surgery that which making this method dangerous. In contrast, non-invasive methods involve measurements of electromagnetic potentials from outside the head. This thesis is concerned with electroencephalography (EEG), which is a non-invasive method of recording voltage measurements from the scalp surface.

Other techniques used to map brain activation are functional magnetic resonance imaging (FMRI), positron emission tomography (PET) scan, and MagnetoEncephaloGraphy (MEG). FMRI measures the changes in blood flow level (blood oxygen level) in the brain [12]. A PET scan is an imaging test that helps reveal how tissues and organs are functioning and uses a radioactive drug (tracer) to show this activity. It is useful in discovering or evaluating some cases such as some cancers, heart disease and brain disorders [13]. These approaches have relatively poor time resolution but excellent special resolution when compared to EEG. MEG is an imaging technique that measures the magnetic field produced by electrical activity [14]; EEG can be simultaneously recorded along with MEG.

2.2.1 Concept of EEG

Electroencephalography (EEG) is the method of recording of electrical activity along the scalp. EEG measures voltage fluctuations resulting from ionic current flows within the neurons of the brain. The brain's electrical charge is maintained by billions of neurons are electrically charged by membrane transport proteins that pump ions across their membranes [8].

EEG is the most studied potential non-invasive interface for several reasons: its fine temporal resolution, portability, ease of use and low set-up cost. The disadvantages of using EEG as a brain-computer interface are the technology's sensitiveness to noise and the extensive training required before users can work the technology. BCIs that use EEG for data collection are easy setup, can be deployed in numerous environments, prefer for their lack of risk and inexpensive.

EEG signals contain five major frequency bands distinguished by the number of waves per second as shown in Figure 2.2. These frequency bands from high to low frequencies, respectively, are Gamma, Beta, Alpha, Theta, and Delta [15]. Each band relates to particular tasks as described in Table 2.1, which use in most studies whether in medical fields or in pattern recognition fields especially emotion recognition as shown in next chapter.

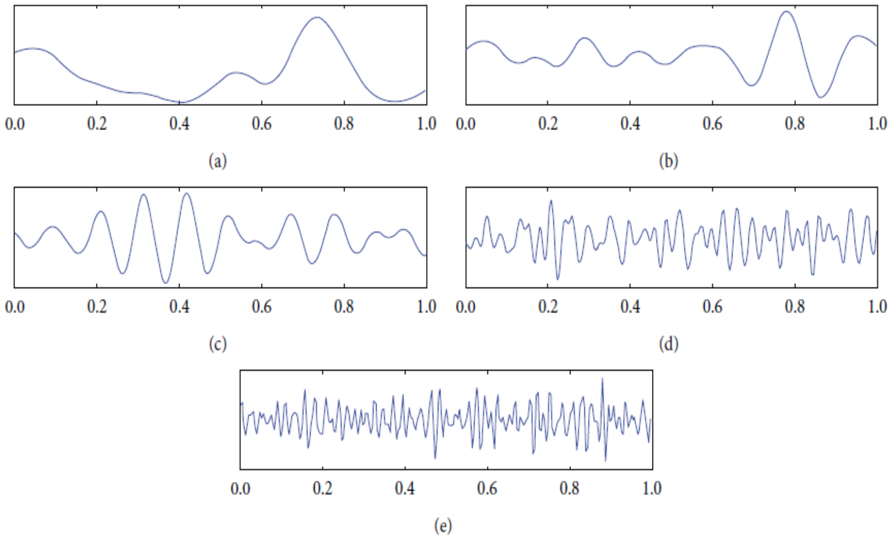


Figure 2.2 Brainwaves: (a) Delta, (b) Theta, (c) Alpha, (d) Beta, and (e) Gamma [16].

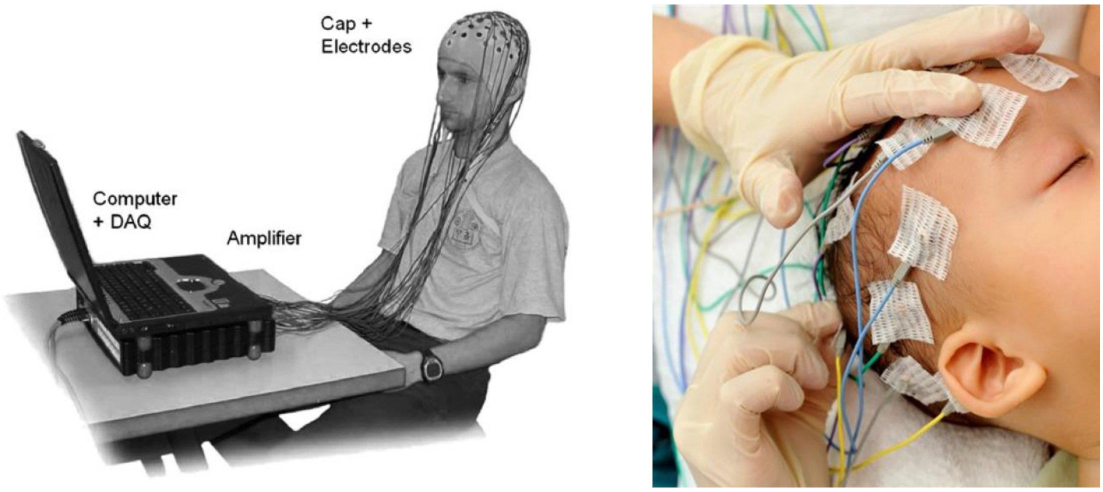
TABLE 2.1 Five Types of Brain Signals [15].

Brain signal	**Frequency (Hz)**	**Description**
Delta	0 ~ 3	Associated with the deep stage of sleep.
Theta	4 ~ 7	Associated with drowsiness.
Alpha	8 ~ 15	Associated with relaxed, alert state of consciousness.
Beta	16 ~ 31	Associated with active, worried thinking, and external focus.
Gamma	32 ~ 64	Associated with working memory and attention, it is an extension of the Beta band.

2.2.2 Measuring EEG Signals

As we mentioned before, EEG is a non-invasive method of recording voltage measurements from the scalp surface through electrodes placed on the head. These electrodes link with a computer by cable or wireless. In cable case, as shown in

Figure 2.3(a), electrodes are fixed on the cap and linked with cables that transmit the signals from the electrodes to the amplifier, and then to the computer. The amplifier is a device converting the brain signals from analog to digital format. The electrodes number varied depends on the used technique. Some types of this technique place electrodes direct on the head without cap and use plaster to fix them as shown in Figure 2.3(b). The disadvantages of this technique are non-portable and take the time to place the electrodes that were overcome in wireless technique.



(a) (b)

Figure 2.3 Electrodes connect with a cable to measure EEG signals [7].

In a wireless case, see Figure 2.4, the electrodes are sensors designed to work on bare skin and made from a hydrogel encased inside a conductive membrane. These sensors are put inside a pod equipped with an amplifier [17]. This technique is based on the EPOC headset for recording EEG measurements and a software suit that processes and analyzes the data. It started with 64 electrodes and then reduced to 14 then to 5 that considers the last version, plus two reference electrodes in all versions. Each channel represents the difference between a particular electrode and a designated reference electrode. Consequently, each electrode gives one channel that has the same electrode name. The name of the electrode is a combination of character and number, where the character indicates to the certain region (lobe) of the brain, and the number indicates the certain position on that particular lobe, Figure 2.5 shows the regions of the brain. The number also indicates to which part of the right/left homologues hemispheres of the brain an electrode is located, where even numbers indicate to the right hemisphere and odd numbers indicate to left hemisphere [8]. For example, T7 means the electrode locates in Temporal lobe in left hemisphere at position 7.

(a) 64 channels[17]   (b) 14 channels[18]   (c) 5 channels[18]

Figure 2.4 Wireless electrodes to measure EEG signals.

The placement of the electrodes on the scalp considers an important factor when EEG signals are recorded for a range of subjects, if the electrodes placed randomly then comparing results will be useless practically. Therefore, a standard named “10-20 system” was introduced [19]. It is the current working electrode placement system when recording EEG signals on human, and has been adopted in this thesis. Figure 2.6 shows partition principle of this system.

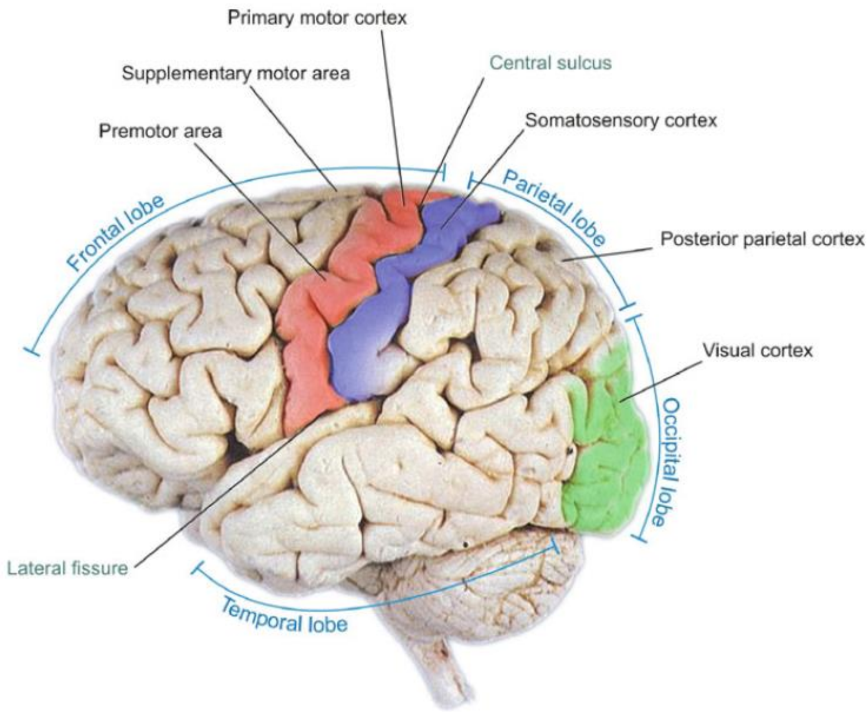


Figure 2.5 Regions of brain [7].

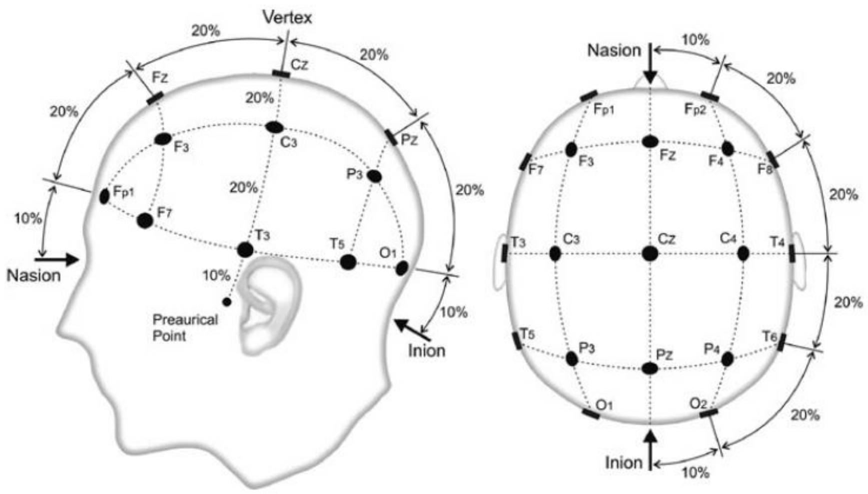


Figure 2.6 The international 10-20 system [7].

This thesis uses a wireless EMOTIV headset that contains a rechargeable 12-hour lithium battery, 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (CMS/DRL as references), and a gyroscope. It has an effective bandwidth of 0.16- 43Hz, 128 sampling rate, and digital notch filters are at 50Hz and

60Hz (Figure 2.4(b)). The place of these electrodes on the scalp according to 10-20 system illustrated in Figure 2.7.

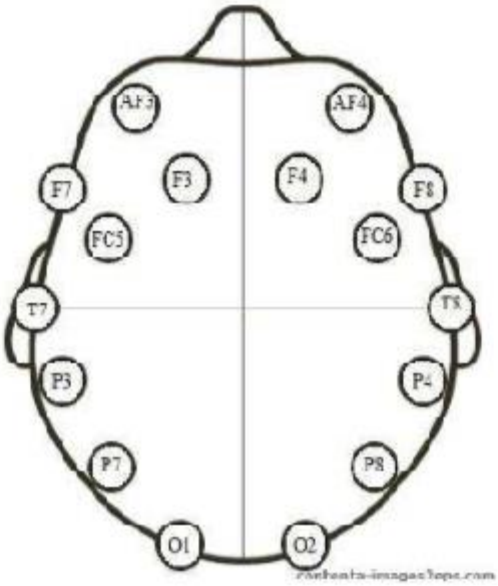


Figure 2.7 The 14 EPOC Headset. Also, there is a Common Mode Sense (CMS) electrode in the P3 location and a Driven Right Leg (DRL) electrode in the P4 location, which form a feedback loop for referencing the other measurements [20].

2.3 EEG-Based BCI

Although the idea of using EEG signals as input to the BCIs has existed since the initial conception of BCIs, actual working BCIs based on EEG input have only recently appeared [8]. Most of EEG-based BCI systems follow a similar paradigm in reading EEG signals, analyzing these signals, translating them into device output, and giving some feedback to the user, see a general diagram of BCI system in Figure 2.1. Figure 2.8 shows EEG-based BCI components in more details.

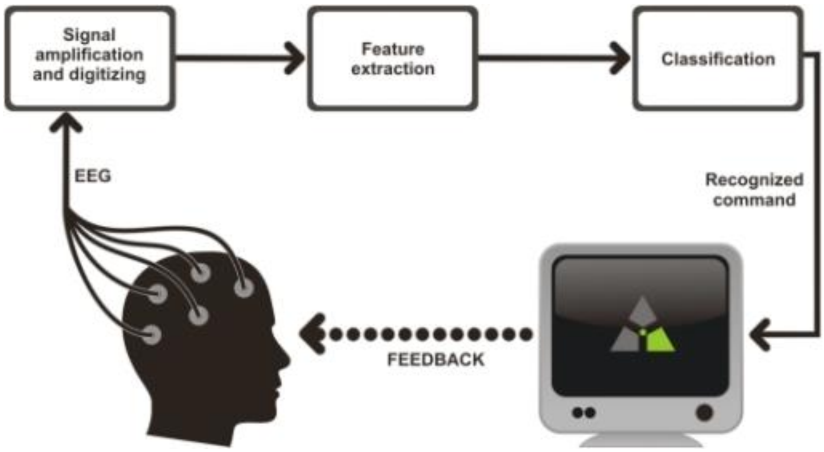


Figure 2.8 EEG-based BCI components in detail [21].

The main difficulty in creating an EEG-based BCI is extract the features and classification of EEG data that must be done in real-time. Feature extraction separates useful EEG data from a huge data that mix with noise, and simplifies that data so that classification. The problem of trying to decide what the extracted data represents can occur. There is no best way of extracting features from EEG data; modern BCIs often use several types of feature extraction including wavelet transforms, Fourier transforms, and various other types of filters.

EEG-BCIs can be classified as either synchronous or asynchronous. The computer drives synchronous systems by giving the user a cue to perform a certain mental action and then recording the user's EEG patterns in a fixed time-window. Asynchronous systems, on the other hand, are driven by the user and operate by passively and continuously monitoring the user's EEG data and attempting to classify it on the fly. Synchronous protocols are far easier to construct and have historically been the primary way of operating BCI systems [22].

EEG-BCI systems have made incredible progress in recent years. By 2000, researchers had created a thought-translation device for completely paralyzed patients that allowed patients to select characters based on their thoughts, although the character selection process was time-consuming and not perfectly accurate [23].

By 2008, researchers collaborating from Switzerland, Belgium, and Spain created a feasible asynchronous BCI that controlled a motorized wheelchair with a high degree of accuracy though again the system was not perfect [24].

Today, the 2010 DARPA budget has allocated $4 million to develop an EEG-based program called Silent Talk, which will allow user-to-user communication on the battlefield without the use of vocalized speech through analysis of neural signals [25].

State-of-the-art EEG-based BCIs are a cutting-edge emerging technology, and researchers are constantly developing newer and more accurate algorithms to make BCIs simpler and more effective than ever before.

2.4 Pattern Recognition and Machine Learning in BCI Systems

Recognition of intended commands from brain signals presents all the classic challenges associated with any pattern recognition problem. These challenges include noise in the input signals, variations and ambiguities in the input data, features extraction, as well as overall recognizer performance. A BCI system designed to meet specific customer performance requirements must deal with all of these challenges.

Recognizing brainwave patterns for BCI presents an interesting pattern recognition problem. It can be determined that the BCI is a classification problem, and like any classification task, it operates in two phases: training and testing.

In the training phase, the subjects perform different tasks such as imagine moving hands, feet, and doing simple math and the BCI is trained to recognize one task from another. In the testing phase (classifying phase), the already trained BCI is applied on new data sample to determine the intended class label (intended task).

BCI systems are further complicated by the fact that there is no standard way of classifying the extracted data. Various means including neural networks, threshold parameters, and various other types of pattern recognizers are employed to try to match the input data to known categories of EEG archetypes [26]. Furthermore, researchers have also relied on unsupervised learning algorithms to find natural clusters of EEG segments that are indicative of certain kinds of mental activities with varying degrees of success [22, 27].

Feedback is essential in BCI systems as it allows users to understand what brainwaves they just produced and to learn behavior that can be effectively classified and controlled. Feedback can be in the form of visual or auditory cues and even haptic sensations, and ongoing research is still attempting to figure out the optimal form feedback should take [28].

An accurate recognition system must be able to accommodate variations introduced by the different brain patterns of individuals as well as variations in the brain patterns caused by the use of different mind state like being tired or having less concentration. This coupled with numerous challenges like the quality of EEG signals, its non-stationary nature, common EEG artifacts and the feature dimensionality presents a significant challenge to EEG-based BCI systems.

Chapter 3

Emotion Recognition in BCI

3.1 Introduction

Emotions are researched in various scientific disciplines such psychology, neuroscience, and linguistics. They affect our behavior, thinking, and mood, which often play a significant role in shaping up of our personality. In psychology and philosophy, emotion is a subjective, conscious experience characterized primarily by psychological expressions, biological reactions, and mental states. Emotion is often the driving force behind motivation whether positive or negative [29]. It is understood that different causes result in different emotions and hence different actions, and vice versa.

The emotional behavior of human natural is multimodal, complex and subtle. In daily life, people naturally communicate through language, vocal intonation, hand gesture, body movement and posture, facial expression, and head movement. They own a refined mechanism for understanding and interpreting information conveyed by these behavioral hints [30], and then behave in the best manner to improve the communication in a certain situation. In the past few decades, many studies have been done to recognizing emotions through these methods. However, these methods are not reliable because people can conceal their feelings.

To overcome this problem, researchers introduced other methods into emotion recognition field such as electromyography (EMG), skin temperature, brain signals, respiration rate, and heart rate [31]. In particular, electroencephalogram (EEG) signals enable us to know the inner emotions which are reliable and cannot be hidden, and which have been adopted in this thesis. They cause the voltage changes in the brain which are considered as the center of emotions [30]. Emotion recognition through EEG signals are based on detecting and classifying specific activities patterns among brain signals that are associated with specific task or event.

3.2 Emotion Models

There are three major models that used to represent emotion according to the research in psychology: (1) discrete/basic emotion, (2) dimensional model, and (3) appraisal-based model [32]. The basic emotion model is supported by findings of Eckman and Friesen [33]. They studied facial expression in different cultures and provided evidence in support of the hypothesis that the association between discrete emotions and particular facial muscular patterns is universal. Those expressions are consistent across different cultures although the influence of circumstances and different social settings, and which are six independent emotions: sadness, happiness, fear, anger, disgust, and surprise. Although psychologists have proposed different categories of emotions, ranging from 2 to 18 [34, 35], there has been considerable agreement on this six emotions. To date, Eckman's theory on universality and interpretation of nonverbal emotional expressions in the frame of basic emotion model has been the most commonly adopted approach in research on automatic effect recognition [30].

In the dimensional model, emotional states are not independent of each another; on the contrary, they are related to one another methodically. Russell in [36] proposed that each basic emotion represents a dipolar entity being a portion of the same emotional continuum which is arousal and valence, as shown in Figure 3.1. The arousal dimension indicates how activity emotion is, and ranging from relaxed (low level) to excited (high level). The valence dimension indicates how feeling emotion is, and ranging from unpleased (negative feeling) to pleasure (positive feeling). The proposed emotional space consists of four quadrants: low positive, high positive, low negative, and high negative. In this way, as argued by Russell, all emotions can be characterized by their valence and arousal, and different emotional labels could be plotted at different positions in this two-dimensional space. Therefore, this model might be named valence-arousal model.

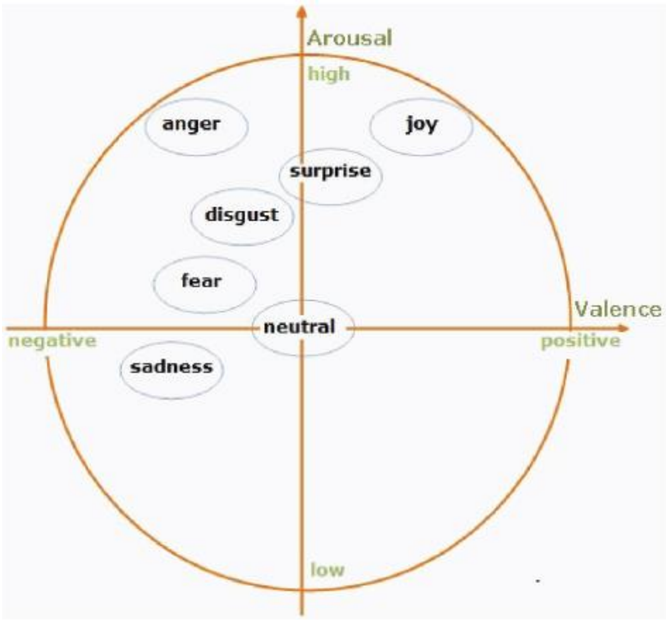


Figure 3.1 Bi-dimensional valence-arousal model [30].

The appraisal-based model, which can also be seen as an extension of the dimensional approach, is another set of psychological models that is introduced by Scherer and colleagues, referred to as componential models of emotion, which are based on appraisal theory [37]. It claimed that emotions are generated through continuous, recursive subjective appraisal of both our internal state and the state of the outside world [32]. This model estimates emotions through changes in all relevant components including physiological reactions, motivation, cognition, motor expressions, and feelings. The advantage of this model is that it does not limit emotional states to a constant number of discrete categories or a few basic dimensions. Instead, it focuses on the variability of different emotional states that produced by different types of appraisal patterns [30]. However, this model requires complex, multicomponent and sophisticated measurements of change, which making use it for automatic emotion recognition an open research question.

3.3 EEG-Based Emotions Recognition

In recent years, the research on EEG-based emotions recognition acquired great attention in interdisciplinary fields from psychology to engineering, including basic studies on emotion theories and emotional applications, which turn enhances the BCI systems with the ability to detect, process, and respond to users' emotional states using physiological signals [38].

3.3.1 Procedure of emotion recognition

The procedure of emotion recognition, as shown in Figure 4.1, includes several steps. The first step is stimulus, which considers the important step to building a good predicted model for emotions. It can be by audio, picture, movie, or combine them. The participant will be exposed to stimuli to trigger a targeted emotion, and during that, the EEG signals are recorded. Before analyzing EEG signals, step 3, the artifacts and noise are removed, and then relevant features are extracted. Some parts of features will use to train a classifier while the rest use to test it. The result of classifier uses to learning the machine.

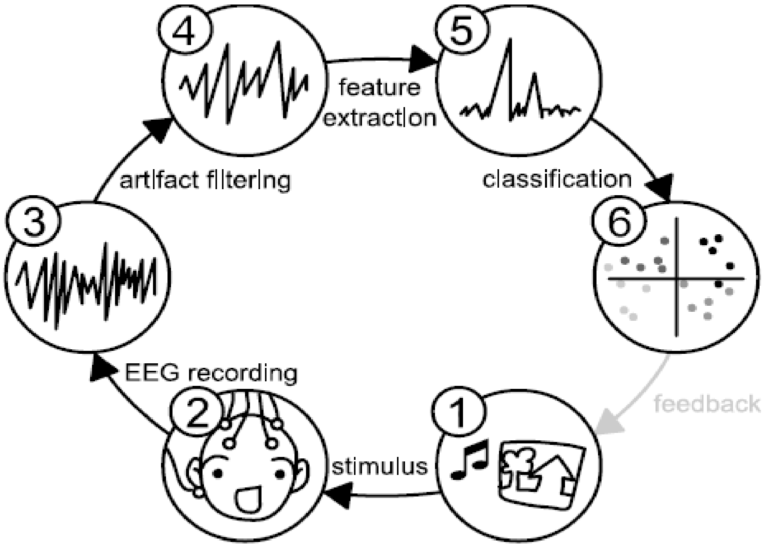


Figure 3.2 The procedure of emotions recognition [39].

3.3.2 Related Work

The recognition of emotions can be performed from the facial expressions, voice and physiological signals, among others. Since the focus of this work is the definition of processing techniques of EEG signals to provide better results in the classification of the brain signals into emotions, this section presents works based on EEG signals for recognition of emotions.

With the fast development of embedded systems and micro-nano technologies, it is now possible to port BCI systems from the laboratory to real-world environments. Many advanced dry electrodes and embedded systems are developed to handle the wearable, portability, and practical use of these systems in real world applications. Various studies in computing community try to build effective models to estimate emotional states based on EEG features.

EEG signals and facial expressions were used together in [40] for recognizing the emotions. It proposed a system to detecting the emotion (positive or negatives) that generated from hearing a particular song to the evaluation of acoustic quality in a concert hall. EEG signals were acquired by electrodes placed in the temporal region of the brain, and facial expressions were acquired from video images. Because of this work, the researchers determined that it not be possible to distinguish the type of emotion from the signals used together.

Since music could influence the mood and affect the health, [41, 42] classified emotion during music listening. In [41], support vector machine was used to classify four emotional states (anger, joy, pleasure, and sadness). The researchers used the electrodes that placed near the frontal and the parietal lobes to deriving the features. To find an optimal set of emotion-specific features, they used Power Spectral Density (PSD) to all channels (PSD30), PSD for symmetrical electrodes (PSD24), PSD resulting from subtracting PSD of symmetrical electrodes pairs (DASM12), and resulting from divide (RASM12). They found that DASM12 was a sensitive metric for describing brain dynamics in response to emotional states and gave the highest accuracy from among others at 82.29%. In contrast, [42] found that the recognition by theta and alpha on emotion has similar performance, and frontal alpha and frontal midline theta play important roles in emotional processing.

Yisi Liu et al. in [43] proposed a real-time fractal dimension based algorithm for classification of brain electrical signals in human emotions. This algorithm was based on the model of fractal dimension. The researchers used some songs in the first experiment and sounds from the International Affective Digitized Sounds (IADS) database in a second experiment to induce certain emotions in the participants of this study. The brain signals were acquired from three channels, FC6, F4, and AF3. Through the channel FC6 was possible to classify emotions regarding the level of excitement, the channels AF3 and F4 were used in the classification of emotions with respect to valence. The six basic emotions were recognized and identified them in the bi-dimensional valence-arousal graph, as shown in Figure 3.3. The researchers found that in the forebrain of an individual can be identified greater activation in one hemisphere during the feeling of positive emotion and greater activation in the other hemisphere while feeling a negative emotion.

The real-time EEG-based emotion recognition can be applied in many fields such as education, entertainment, and medicine. Yisi Liu and colleagues also implemented three applications, which are an emotional avatar, EEG-based music therapy, and EEG-based music player. The emotional avatar visualizes the recognized emotions with Haptek ActiveX control system, which is a 3D model with predefined parameters for visualizing facial muscles. In the EEG-based music therapy application, the current emotional state of the patient/user is identified, and based on that adjust the music therapy to his need. The emotion state of the patient is continuously checked by his/her EEG in real time, and if the currently running music does not effectively excite the targeted emotion of the therapy, the music is changed to another song; this makes the patient/user does not need to a music therapist. In the last application, songs are categorized into the six emotion types, and through a website, the current emotional state of the user is recognized and then the corresponding song is run.

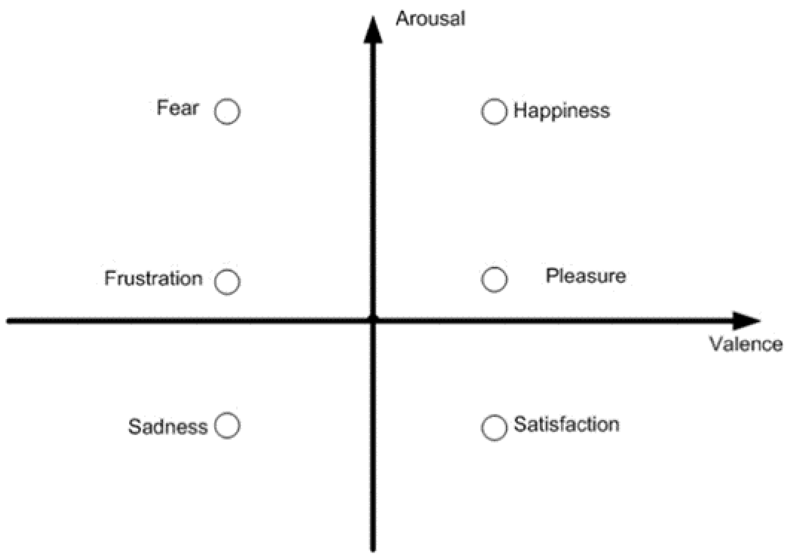


Figure 3.3 Identified the six basic emotions in a Bi-dimensional valence-arousal model.

The aim of [44] was finding the relationship between EEG signals and human emotions during watching movies. It adopted linear- Support Vector Machine (SVM) to classify emotions into two types: positive and negative. By using log band energy feature to all channels and bands, the researchers obtained accuracy 87.53% by using all the features which were 310. They reduced the dimension of features using correlation coefficients and got on accuracy 89.22% using the top 100 and 84.94% using the top 50; this demonstrates that there are some channels that have no effect on recognizing emotions.

All these studies adopted on labeled stimuli which means the acquired emotion is known. Researchers have developed many databases of standard labeled stimuli to elicit certain emotions such as the International Affective Digitized Sound (IADS) [45], the Geneva Affective Picture Database (GAPED) [46], or video. Unfortunately, there is no exist a database of labeled stimuli for the Quran audio clip, and hence, our proposed model depends only on listener's evaluation as a labeled.

As mentioned before, brainwaves consist of five types of waves: Delta, Theta, Alpha, Beta, and Gamma wave. Some studies used Alpha to compare the effect of listening to Quran recitation and listening to music on EEG signals [47, 48] because Alpha is associated with the relaxed and alert state of consciousness while [49] used KDE (kernel smoothing density estimate) as a feature. All those studies showed that listening to Quran gave more relaxing, and alert conditions compare to music. Table 3.1 shows all these studies briefly.

[20] focused only on listening to Quran and classified the emotional state during that into two types: devout and non-devout using arousal-valence model and random forests classifier. It got on best accuracy at 87%, but the average accuracy using 10 fold-cross validation was 62%. Therefore, this thesis aims to develop an emotional based BCI system where the emotional state of the user can be detected and classified into two types of emotions namely, devout and non-devout according to his brain signals and comparing results with it. Non-devout means the listener has not been affected by hearing the Quran. The proposed model is trained using the database of [20] and used two types of features: FD and PSD, and two classifiers: SVM and random forests.

TABLE 3.1 Various Studies on EEG-Based Emotion Recognition.

References	**Year**	**Participant #**	**Stimulus**	**Emotion**	**Channels**	**Feature**	**Classifier**	**Accuracy/ Result**	**Real time**
[40]	2009	3	audio	positive, negative	T3 , T4	PSD for Alpha and Beta wave	represent results on compass map	it was not possible to distinguish the type of emotion from the signals used together	No
[41]	2010	26	audio	joy, anger, sadness, pleasure	30 channels	PSD	SVM	82.29%	No
[43]	2011	10 in first experiment and 12 in the second experiment	audio	The six basic emotions	FC6 , F4 , AF3	FD	fractal dimension based algorithm	Implemented novel fractal dimension based algorithm for recognition of emotions from EEG in real time	Yes
[44]	2011	6	movie clips	positive, negative	62 channels	log band energy of each channel	linear- SVM	87.53%	No
[42]	2013	28	audio	positive emotion	Five channels located in the frontal lobe	PSD to Alpha and Beta	SVM	More than 80%	Yes
[47]	2011	14	audio	studying the	F3, F4, Cz,	analysis Alpha	SPSS	listening to	No

				change in Alpha wave	P3, P4, O1, O2, T3 and T4	wave		Quran can help a person always in relaxing condition compared with listening to hard rock music.	
[48]	2012	28	audio	It only compares the brainwave patterns of Alpha	They used the Biomedical Research Laboratory for Human Potential	analyzing data of both interview session and EEG of Alpha band	SPSS	there is an increment of 12.67% during listening to Al-Quran and 9.96% for classical music	No
[49]	2014	3	audio and movie clips	basic emotions based on valence and arousal values	F3, F4, C3, C4 for EEG, and T3, T4, P3, P4 for ECG	KDE	A supervised artificial neuron network algorithm	the subjects more relaxed while listening to Quran recitation.	No
[20]	2014	14	audio	devout, non-devout	FC6, F4, AF3	FD	random forests classifier	62%.	Yes

* Power Spectral Density (PSD), Fractal Dimension (FD), Support Vector Machine (SVM), Statistical Package for the Social Sciences (SPSS), kernel smoothing density estimate (KDE).

3.4 The Fractal Dimension Approach

We used Higuchi algorithm to calculate FD in this work. It calculates fractal dimension value of time-series data X(1), X(2), … , X (N) by constructing new time series as follows [50]:

$$X_k^m : X(m), X(m+k), \ldots, X\left(m + \left[\frac{N-m}{k}\right] \cdot k\right)$$
$$(m = 1, 2, \ldots, k)$$

Where *m* is the initial time and *k* is the interval time. For example, if *k* = 3 and N = 50, the newly constructed time series are:

$$X_3^1 : X(1), X(4), \ldots, X(49), X_3^2 : X(2), X(5), \ldots, X(50),$$
$$X_3^3 : X(3), X(6), \ldots, X(48).$$

k sets of $L_m(k)$ are calculated as follows:

$$L_m(k) = \frac{\left\{ \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left| X(m+ik) - X(m+(i-1)\cdot k) \right| \right) \frac{N-1}{\left[\frac{N-m}{k}\right] \cdot k} \right\}}{k}$$

where $L(k)$ denotes the average value of $L_m(k)$, and a relationship exists as follows:

$$\langle L(k) \rangle \propto k^{-D}$$

Then, the fractal dimension can be obtained by logarithmic plotting between different *k* and its associated $L(k)$ [50].

Chapter 4

Proposed Emotional Model

In this work, we are going to develop two models with different features and classifiers, and evaluate them to selecting the best. Both models aim to discriminate between two types of emotion: devout and non-devout during listening to the Holy Quran. As we mentioned in section 3.3.1, the procedure of emotion classification starts by exposing the subject to stimulus and finishes in classification step. The following sections explain each one in detail according to the proposed models.

4.1 Stimulus

Selecting stimuli depend on the targeted emotions. To this end, several databases that contain standard labeled stimuli are developed in the literature (i.e. the expected emotion from stimuli is known). Unfortunately, there is no such database for the Holy Quran audio clips. In [20], 15 verses were selected by experts based on the meaning of these verses to trigger emotion and each verse recited by five different sheiks to became the total stimuli 75. Each participant writes his/her emotion through a Self-Assessment Manikin (SAM) scale to use it as a labeled. These stimuli have used in this work.

4.2 EEG Recording

Recording of EEG signals was done in the master thesis [20]. A detail of this experiment presents in this section. Figure 4.1 explains the structure of this experiment. Recorded data was obtained from 14 male volunteers with age in the range 16 years to 45 years. All participants have no history neurological or psychiatric disease and were from different nationalities. A wireless EMOTIV headset with 14 channels and 128 sampling rate has used to recording EEG signals (see Figure 2.4(b)). Each participant conducted from 6 to 7 trials, different stimuli in each trial where each participant selects one verse from 75 verses. Thus, we have 90 recorded data of raw EEG signals with associated labeled to 90 trials. Each trial started with a silent period of 10 seconds, which will use as a baseline, then recited verse for approximately 1 minute. After finish listening, the participant is asked to write his emotion as a devout level between 1 to 100 and assign it to that trial.

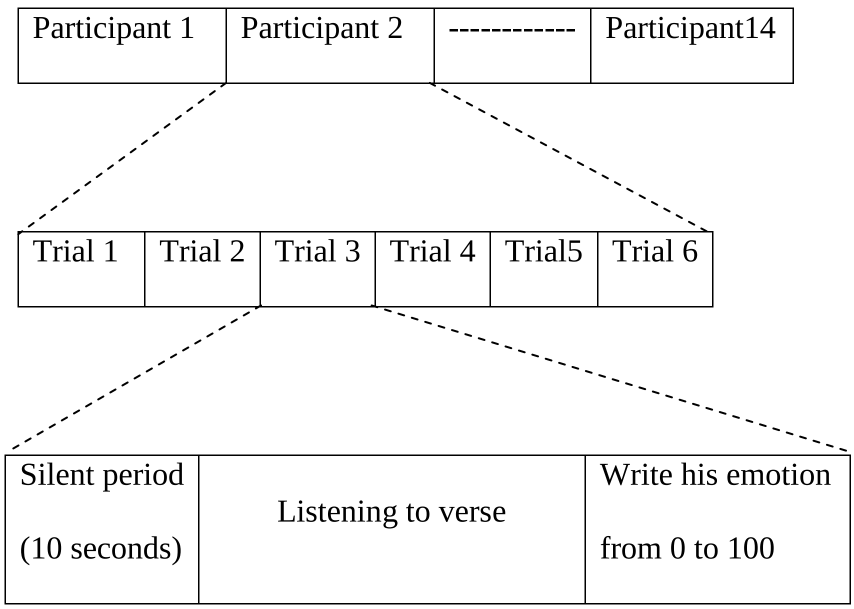


Figure 4.1 Structure of experiment.

The data recording was done in real time through the graphical user interface, see Figure 4.2. The experiment started with a pre-session where the participant is informed about the experiment and the followed steps to complete the experiment successfully; then an approval is signed by the participant. The experiment was performed in a clam room with low lighting. The participant sit on an armchair in front of a PC. The EMOTIV headset was put on the participant's head, and the data acquisition program started on the PC. After ensuring that the EMOTIV electrodes are well connected with the program, the participant wrote the required information and then selected a verse and started listening to it with focusing on the meaning of it. After each recording, the participant wrote his emotion. All recordings were stored in a Matlab file for processing them and extracting the features that have been implemented off-line.

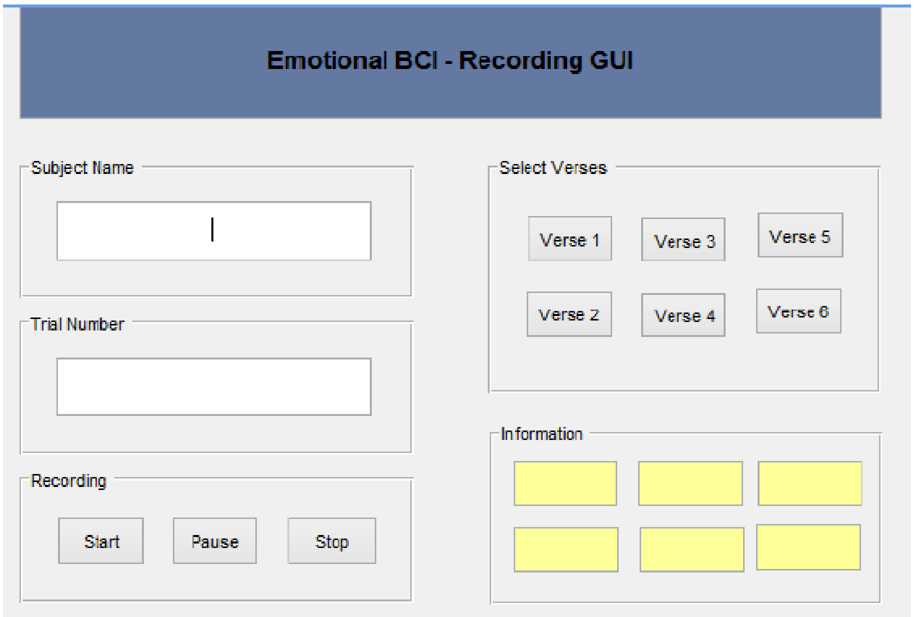


Figure 4.2 Graphical user interface for recording program.

4.3 Preprocessing

Our models discriminate between two types of emotions, which are devout and non-devout, so we will set the class of each trial/recording according to the following formula:

$$\text{Class} = \begin{cases} 1 \ \ (devout) & if\ user\ emotion \geq 70 \\ -1\ (non-devout) & if\ user\ emotion < 70 \end{cases}$$

Therefore, 64 trails assigned with devout emotion while 26 trials are non-devout. To balance between the trials number for the two classes and the trials number for each participant, we took all trials that labeled non-devout and took only 30 trials that have the highest level of devout; each participant has four trials. Consequently, the total trials are 56, 30 devout and 26 non-devout.

The raw EEG signal is typically quite noisy, therefore, it necessary to clean it up. To this reason, a Butterworth bandpass filter of order eight from 2 to 42 Hz is used because of most noisy in the range from 50 to 60 Hz. Then, an average of all channels is used to references the filtered EEG signal by subtracting it from each channel. The last step is to remove baseline of the EEG signal from each channel for each recording. Now the EEG data are ready to extract relevant features as described in next section.

4.5 Feature Extraction

Findings from former studies are a good source to identify key EEG features. In this work, two types of features are extracted which are Power Spectral Density (PSD) and Fractal Dimension (FD). The PSD shows the variation in energy strength in frequency domain while FD shows it in the time domain. Each feature will use to build an independent model, and then the comparison between them are made. The following sections explain the computation way of each feature.

4.5.1 Power Spectral Density

Wavelet translate of four levels was applied to decompose the raw EEG data of each channel into five frequency bands: delta, theta, alpha, beta, and gamma bands which reflect the physical activities, as shown in Table 4.1. For each second (128 points) in all channels and bands, a Fast Fourier Transform (FFT) with non-overlapping window was applied to find PSD per band. The way using for estimate the PSD to that second is the average of the squared absolute value of the magnitude as in equation 4.1:

$$\text{PSD}=\frac{1}{Nyq}*\left(\sum_{f=1}^{Nyq}|FFT|^{\wedge 2}\right) \qquad 4.1$$

where Nyq is the Nyquist frequency (frequency sample/2), and f is the frequency. To investigate the influence of use windowing with FFT, Hann window with length 128 was applied before FFT producing another type of PSD named PSD_withhann. Because EMOTIV device has 14 channels, 70 features were obtained (5 bands * 14 channels) per sample. Therefore, the number of samples per trial equal to the number of recorded seconds to that trial.

TABLE 4.1 Decomposition for EEG Signal

Frequency band	**Frequency range (Hz)**	**Frequency bandwidth (Hz)**	**Decomposition level**
Gamma	32-64	32	D1
Beta	16-31	16	D2
Alpha	8-15	8	D3
Theta	4-7	4	D4
Delta	0-3	4	A4

The features of each participant (F) were normalized to reduce inter-participant variability by scaling between 0 and 1[51], as shown in equation 3.2:

$$normalize(F_i) = \frac{F_i - F_{max}}{F_{max} - F_{min}} \qquad 4.2$$

i =1,2,3,……,number of samples to that participant

Since each participant has 4 trials, there are approximately 200 samples (50 seconds*4) per participant. Due to 14 participants, the total samples obtained from the experiment are 2437 with 70 features for PSD and PSD_withHann similarly, 1196 devout and 1241 non-devout. All samples are labeled whether devout or non-devout depending on the participants' evaluation. Figure 4.3 shows the number of samples per trial.

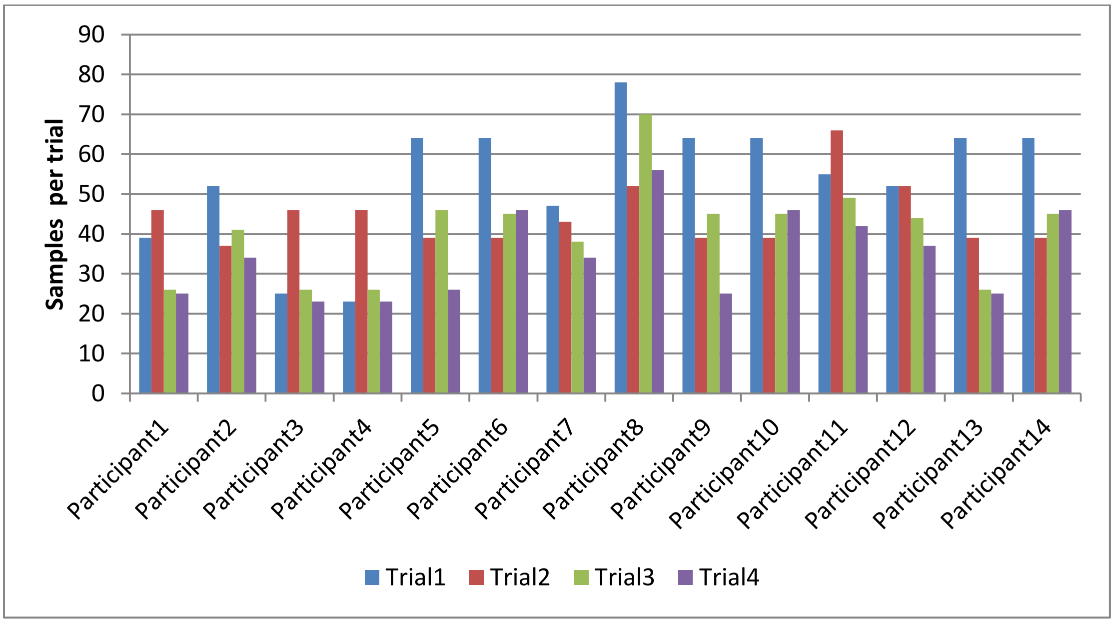


Figure 4.3 Number of samples per trial using PSD.

4.5.2 Fractal Dimension

The FD method was used to calculate values of arousal and valence from treated EEG signals and considers these values features to our FD model. Since arousal represents the excited level diversity of brain state of subject, one electrode FC6 was chosen, which gave good result in literature, to find its value:

$$\text{Arousal} = [FD^{FC6}] \qquad 4.3$$

Many evidences show that the lateralization between the right and left hemisphere associated with emotions [52]. Furthermore, previous works [53, 54] showed that the right hemisphere was more active during negative emotions while the left was more active during positive emotions, but it is not general in all people. According to that and whereas the emotion is more appear in frontal and temporal lobes, two ways are used to compute the valence level. The first way is calculating the difference between FD of the electrode in left hemisphere and FD of the electrode in the right hemisphere. The electrodes AF3, F3, and T7 are selected from left hemisphere while AF4, F4, and T8 are selected from right hemisphere. See Figure 2.7 for the actual position of electrodes on the scalp. The form of valence features are as following:

$$\text{Valence1} = [\, FD^{AF3} - FD^{AF4}] \qquad 4.4$$

$$\text{Valence2} = [\, FD^{F3} - FD^{F4} \,] \qquad 4.5$$

$$\text{Valence3} = [\, FD^{AF3} - FD^{F4} \,] \qquad 4.6$$

$$\text{Valence4} = [\, FD^{F3} - FD^{AF4} \,] \qquad 4.7$$

$$\text{Valence5} = [\, FD^{T7} - FD^{T8} \,] \qquad 4.8$$

The second way is using both values of left and right hemisphere to represent valence feature as follow:

$$\text{Valence6} = [\, FD^{AF3} , FD^{AF4}] \qquad 4.9$$

$$\text{Valence7} = [\, FD^{F3} , \; FD^{F4} \,] \tag{4.10}$$

$$\text{Valence8} = [\, FD^{AF3} , \; FD^{F4} \,] \tag{4.11}$$

$$\text{Valence9} = [\, FD^{F3} , \; FD^{AF4} \,] \tag{4.12}$$

$$\text{Valence10} = [\, FD^{T7} , \; FD^{T8} \,] \tag{4.13}$$

Consequently, the total types of FD features are 10 types, and each one will be used in the independent predicted model to find the best feature and channels among them. Each FD-feature consists of Arousal and Valence (i) where i=1,2,3,…,10, i.e. FD(i)=[Arousal, Valence(i)]. FD values are calculated for the channel on sliding window of size 1024 and 90% overlapping using Higuchi algorithm that explained previously in Section 3.4. The advantage of using the sliding window is that it enables processing in real-time. Therefore, the total numbers of samples per trial depend on the length of input data and the size of sliding window. Due to 56 trials for 14 participants, the total samples obtained from the experiment are 25553, 12299 devout and 13254 non-devout. All samples are labeled whether devout or non-devout depending on the participants' evaluation; Figure 4.4 shows the number of samples per trial.

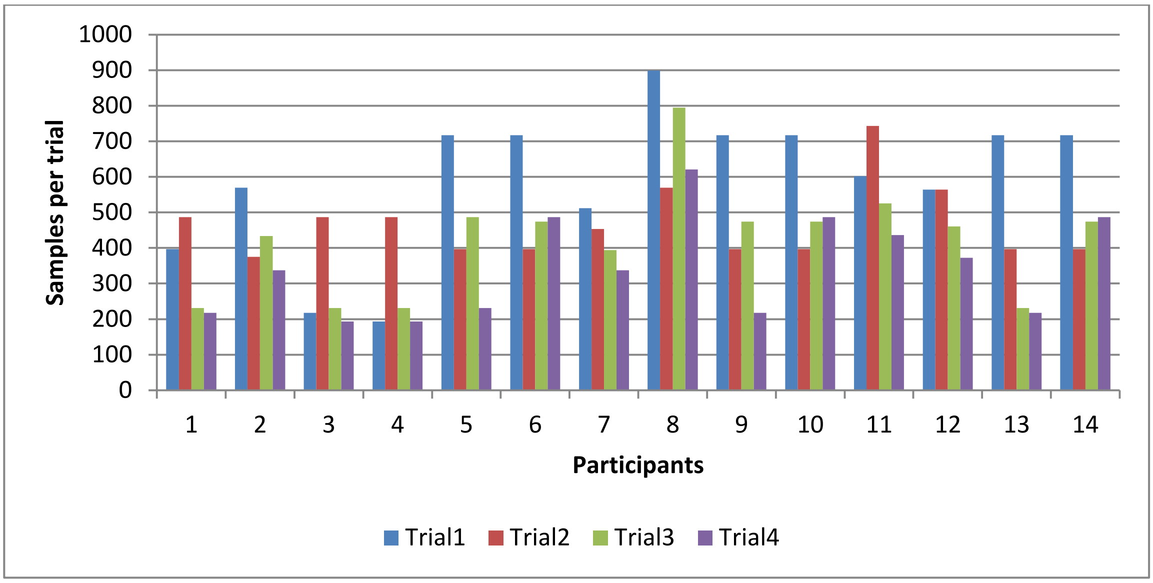


Figure 4.4 Number of sample per trial using FD.

4.6 Classification

To develop our proposed models that discriminate two classes (devout and non-devout), we used two types of classifiers, SVM for PSD feature and Random Forest (RF) for FD feature that gave satisfied results in the literature. SVM is a popular machine learning technique for classification, regression, and other tasks which based on the idea of finding the best hyperplane that represents the maximum margin between the two classes as shown in Figure 4.5. It has four basic kernels: linear, polynomial, radial basis function (RBF), and sigmoid. In this work, the RBF kernel was chosen to some advantages. It can handle the situation when the relation between features and class labels is nonlinear [55]. Also, it needs two parameters only (C, γ) which influence in reducing the complexity of the model. Knowing the best C and γ gives a good performance for the given problem. To this end, cross-validation and grid search method were used to identify them, and then using them to train training set.

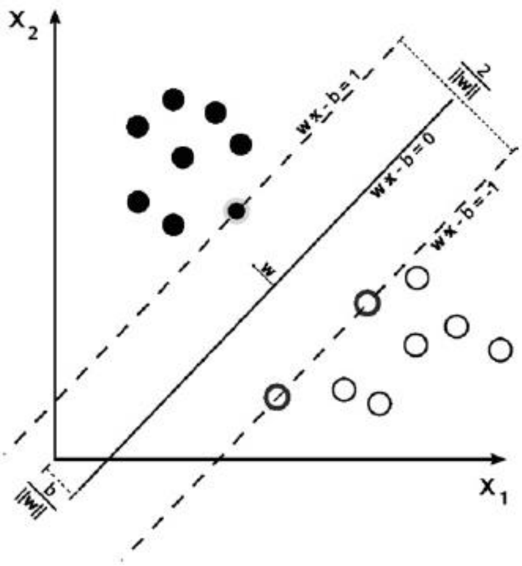


Figure 4.5 Maximum margin hyperplane [56].

A random forest or called random decision forest is a type of decision tree that efficiently handle noisy training data, process large amount of training data, deal with missing feature values, and the underline classification process can be interpreted by explanatory variables [57]. Consider a forest of T trees that trained independently using a different bootstrap sample from the original data; a test point v is simultaneously pushed through all trees until it reaches the corresponding leaves. The final class is given by equation 3.14 [58]:

$$p(c|v) = \frac{1}{T}\sum_{t=1}^{T} p_t(c|v) \tag{4.14}$$

For both classifiers, the 10-fold cross-validation was used to calculate the accuracy of our proposed models. It divides the training set into 10 subsets of equal length. Then, one subset is tested using the model that trained on residual 9 subsets. This procedure is repeated 10 times so that each subset is tested one time. Therefore, the accuracy reported is the average percentage of the data that classified correctly in all folds. To determent the final emotion (class) to each trial, we used leave-one-trial-out cross-validation as following:

- The samples of one trial are set to be a test set and the rest to be a training set,
- Using a training set to build a classification model,
- Then test the model using test set,
- If 50% or more from the samples classified devout, then the emotion of that trial is devout and similarly to non-devout,
- Repeating these steps to all trials such that each trial has used as a test set.

The best model will use to develop BCI in real-time. The implementation of all steps was done on Matlab 2013a. For SVM, LIBSVM 3.21 package has used.

Chapter 5

Results and Discussion

Since there are individual differences in emotion processing by brain [59], we proposed a subject dependent approach in both models.

5.1 Model of PSD-Feature

As mentioned before, we have 2437 samples to 70 features due to 56 trials. The accuracies of using all these features for PSD without hann window and PSD_withHann are 89.86% and 87.07% respectively at γ=0.5 and C=32; Table 5.1 shows that in details. We can conclude that using hann window when EEG signal is decomposed to the five frequency bands does not improve the accuracy of the classifier. Consequently, PSD without hann window has been adopted in the PSD model.

TABLE 5.1 Confusion matrix of PSD without and with hann window.

class	**Hann window**	**devout**	**non-devout**
devout	without	1093	103
	with	1073	123
non-devout	without	148	1093
	with	196	1045

By applying leave-one-trial-out method, we found that 43 out of 56 trials classified correctly while 13 classified incorrectly, i.e. 76.8% of all trials classified correctly. In Figure 5.1, each trial under 50% considers misclassification. Some cases led to varying proportions in classification to each trial:

- A participant wrote his emotion according to the last feeling, not to the most feeling,
- Participant does not estimate his emotion correctly,
- Even if participant wrote the right emotion, this emotion does not generate immediately; it needs some seconds to appear because emotional states change gradually.

Consequently, this result considers reasonable because we depended only on the credibility of the participant in determining his emotion.

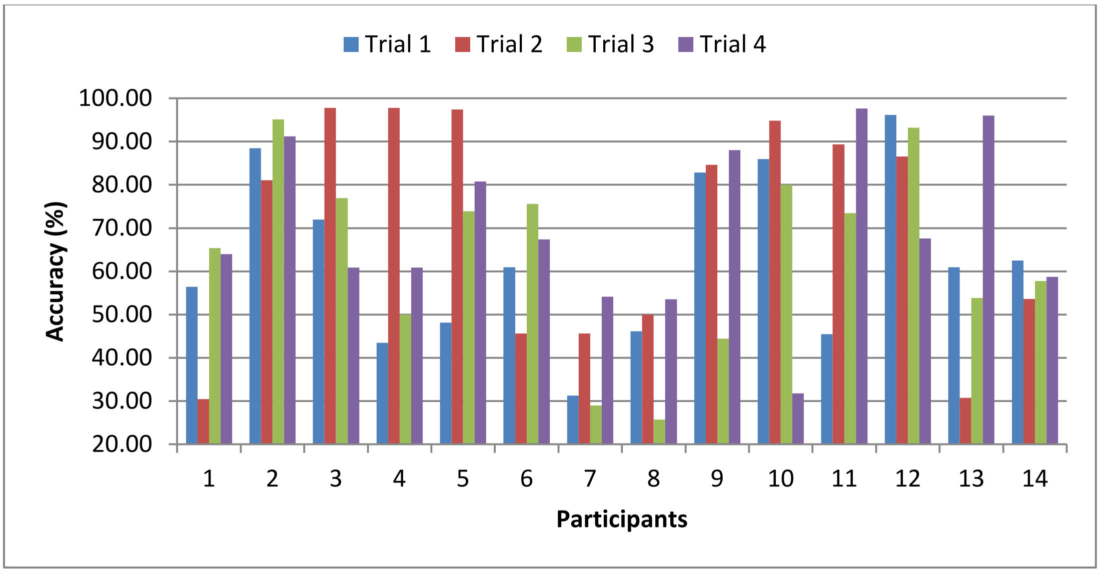


Figure 5.1 Accuracy to each trial to its class.

5.1.1 Varying Pairs of Channels

We compare among the accuracy of each pair of channels (i.e., AF3-AF4, F3-F4, F7-F8, FC5-FC6, P7-P8, T7-T8, and O1-O2) using all the frequency bands at γ=1 and C=128. From Figure 5.2, we found that the pairs T7-T8 and AF3-AF4 gave the highest accuracy at 71.81 % and 71% respectively, which compatible with [60-62]. As a result, we can conclude that temporal and frontal lobes are more related to the processing of these two emotional states than other lobes.

To reduce used features, we combine the pairs of channels start from highest one in accuracy then add the following until reaching all seven pairs. As shown in Figure 5.3, increasing pairs of channels lead to increase the accuracy of the model. As a result, we can use the fifth highest pairs instead of fourteen channels to save computation time where the number of features becomes 50 rather than 70.

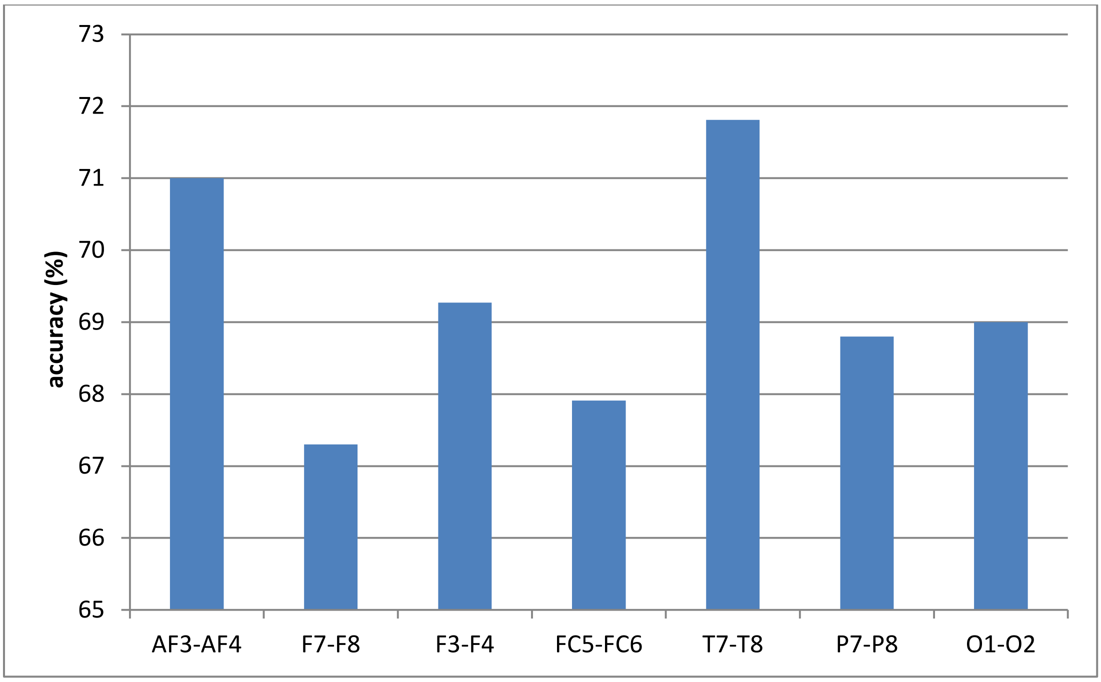


Figure 5.2 Accuracy to each pair of channels.

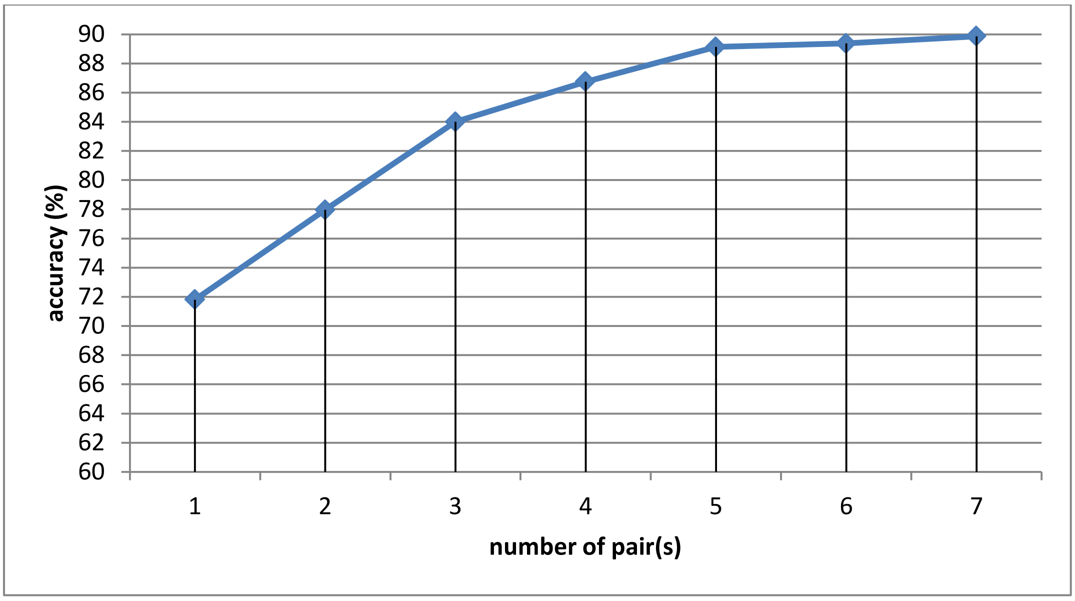


Figure 5.3 Accuracy when reducing pairs of channels.

5.1.2 Varying Frequency Bands

We compare among the accuracy of each frequency band (Gamma, Beta, Alpha, Theta, Delta) using all channels. From Figure 5.4, we found that Alpha and Beta bands gave the highest accuracy at 79.28% and 79.15% respectively followed by Gamma band at 77.92%. Alpha gave the highest accuracy because it associated with relaxed, alert state of consciousness, and as we know listening to the Quran relaxes the heart. As a result, we can conclude that bands that have high-frequency bands are more related to the processing of these two emotional states than others. This conclusion is compatible with [60] [61].

To reduce used features, we combine the frequency bands start from highest one in accuracy then add the following until reaching all frequency bands. As shown in Figure 5.5, increasing frequency bands lead to increase the accuracy. As a result, we can use the three highest frequency bands instead of all bands to save computation time where the number of features become 42 rather than 70.

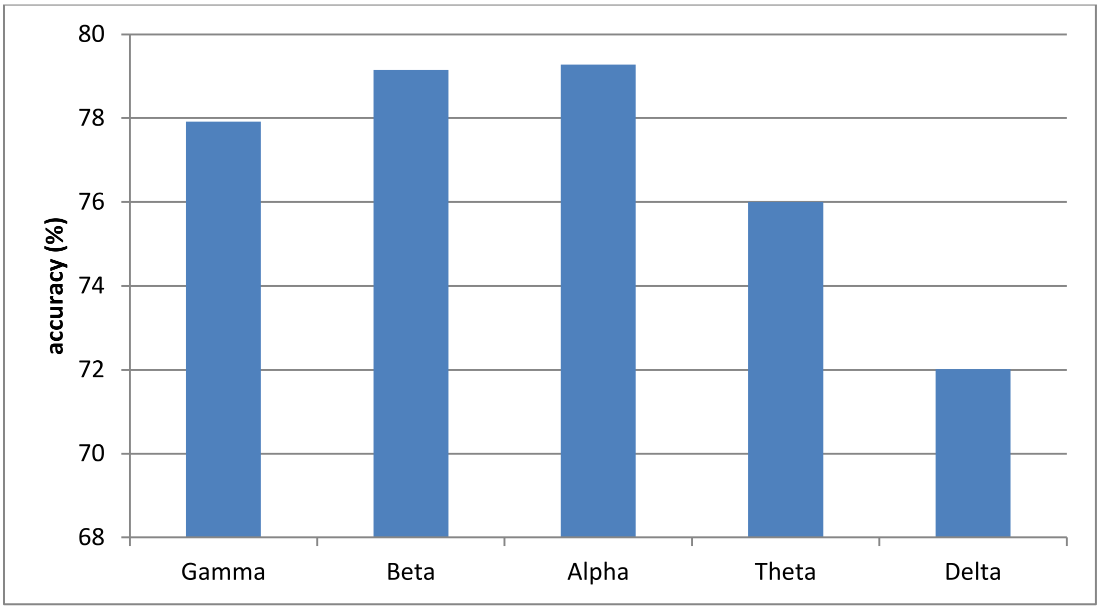


Figure 5.4 Accuracy to each frequency band.

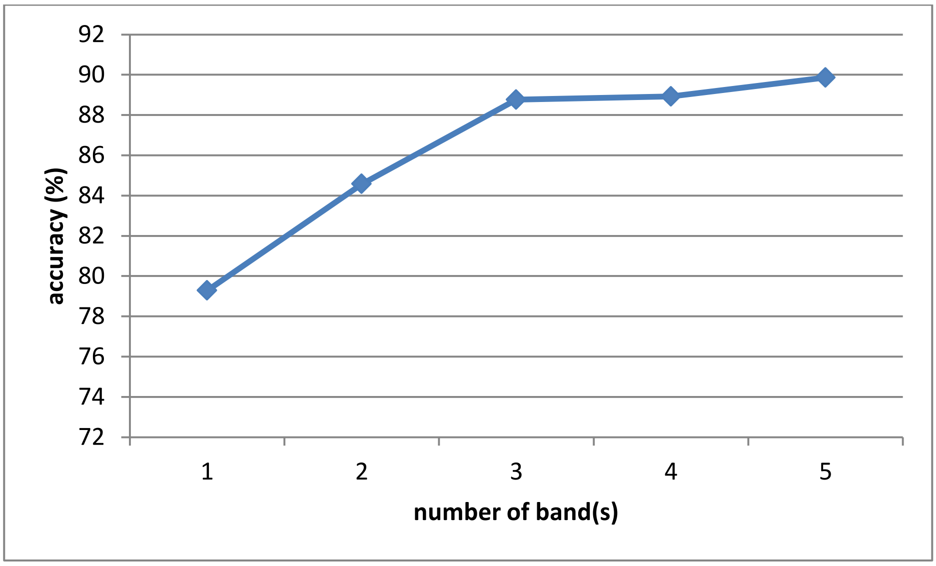


Figure 5.5 The accuracy when reducing the number of frequency bands

5.1.3 Reduce Pairs and Frequency Bands

To investigating whether we can reduce the features with keeping performance high or not, we used the pairs and bands that gave accuracy 84% and over (3 pairs to

6 pairs and 2 bands to 4 bands), as shown in Figure 5.6. We found that using the highest six pairs with highest four bands gave accuracy approximately similar to using all pairs and bands at 89.04% with 48 features. As you observe, using the five highest pairs and all bands gave accuracy higher than 89.04%, but the number of features is also higher. As a result, we used pairs AF3-AF4, F3-F4, FC5-FC6, P7-P8, T7-T8, and O1-O2 with Gamma, Beta, Alpha, and Theta bands to building the model of PSD. Figure 5.7 shows the accuracy of this model for each trial to its class for all participants which is the same result of using all pairs and bands whence the number of trials that classified correctly.

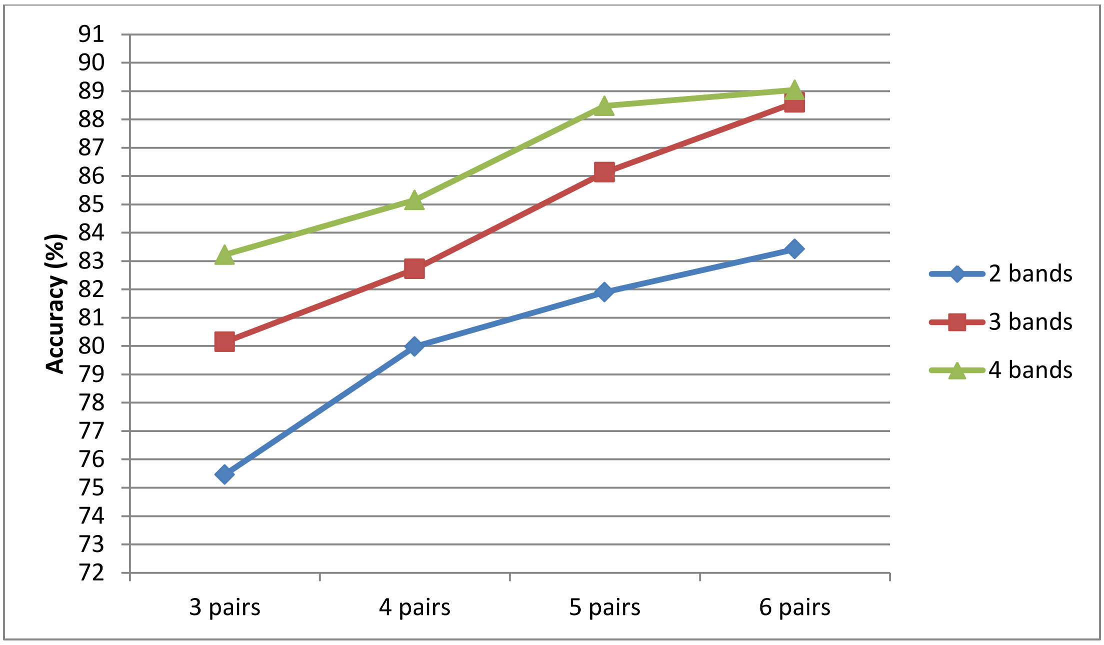


Figure 5.6 The accuracy when reducing the number of pairs and bands.

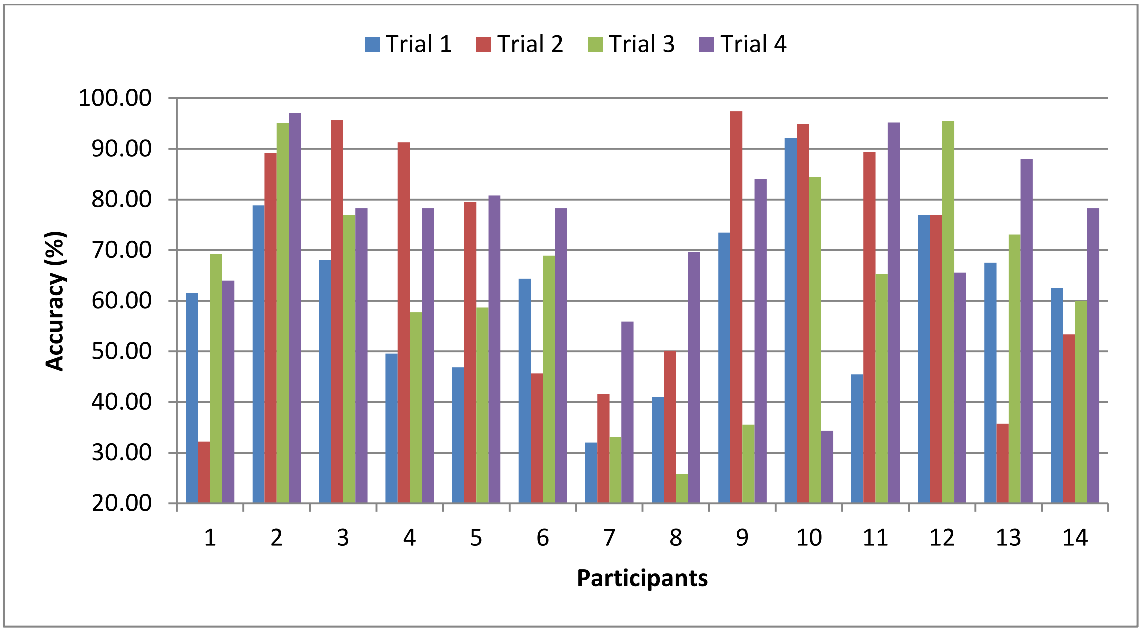


Figure 5.7 The accuracy to each trial to its class using four bands and six pairs.

5.2 Model of Fractal Dimension

Table 5.2 shows the accuracy of each independent FD model for all trials to all participants where each model uses one type from the ten features previously mentioned in section 4.5.2. We found that using both values of the valence, left and right hemisphere; give better accuracy than using the difference between them in all cases. T7 and T8 electrodes have adopted in our FD model because gave the highest accuracy. Although many researchers [20, 50, 63] adopted on AF3 and F4 to find valence level, we found that T7 and T8 are more suitable to find it than others. Electrodes T7 and T8 also gave the best accuracy than other electrodes with PSD feature as explained in the previous section.

TABLE 5.2 Classification Accuracy for each Model

Channels / Valence	AF3-AF4	AF3-F4	F3-AF4	F3-F4	T7-T8
[left - right]	72.88%	74.23%	73.98%	71.31%	75.57%
[left , right]	91.48%	91.97%	92.62%	91.28%	92.94%

Figure 5.7 explains the classification accuracy to each class when the valence level represents the difference between FD values of the left and right hemisphere while Figure 5.8 explains it when the valence level represents the FD value of the left hemisphere and FD value of the right hemisphere. In both figures, T7 & T8 achieved the less difference between the accuracy of the two classes which making them the best electrodes to calculate valence level.

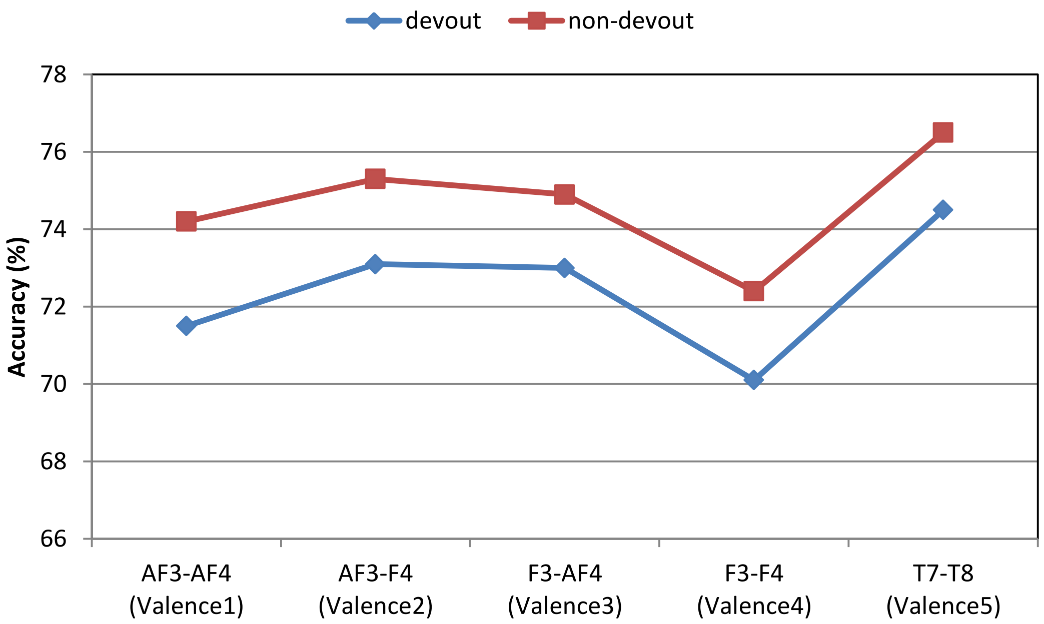


Figure 5.8 Classification accuracy to each class using valence1 to valence5.

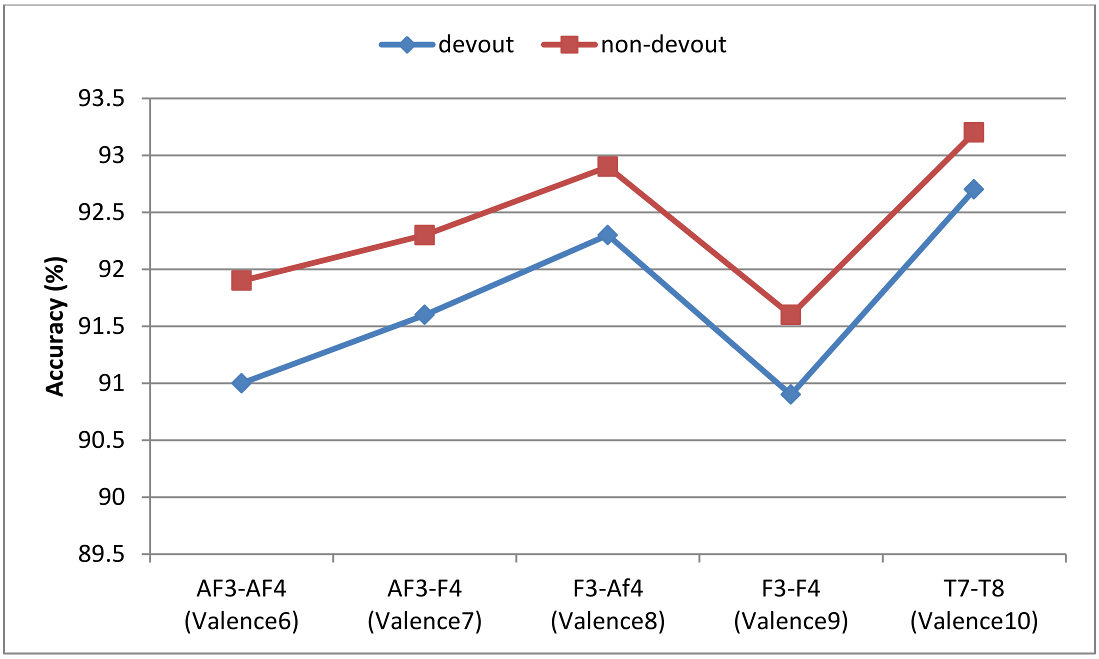


Figure 5.9 Classification accuracy to each class using valence6 to valence10.

According to that, we built the model of FD depending on arousal level from FC6 and valence level from T7 and T8. We assume that the devout emotion is a case of happiness or fear in sometimes which locates in the upper half of the two-dimensional emotional model, see Figure 3.3. By seeing to the histogram in Figure 5.10, we found that the arousal level to all samples is high, that means the brain state of the listeners during listening to the Quran was active, while the valence level distributed between positive and negative, in the range -0.4 to 0.4. In Figure 5.11, the average of arousal and valence values to each trial were mapped to the 2D Arousal-Valence model. We can see the devout class is more on the positive side while non-devout class is more on the negative side which supports our assumption.

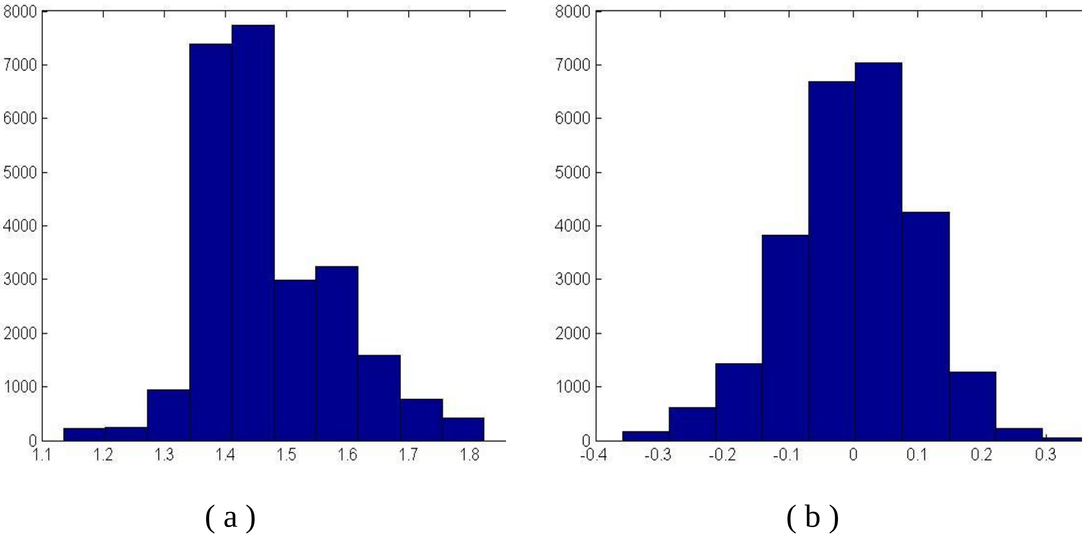


Figure 5.10 Histogram of (a) Arousal and (b) Valence.

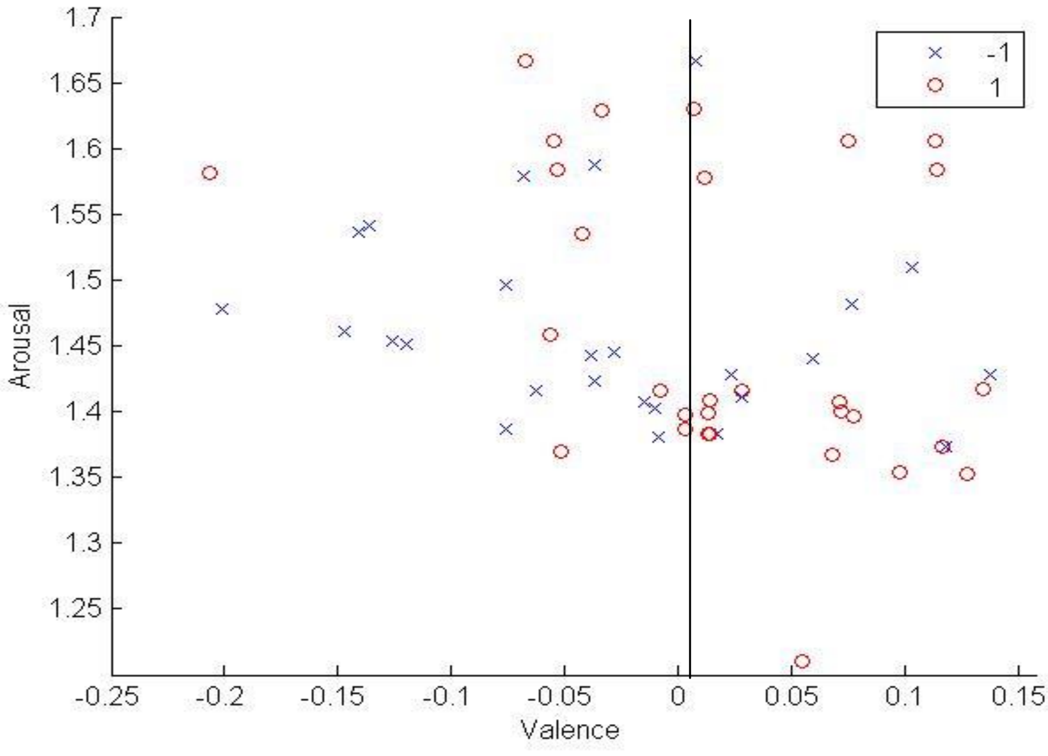


Figure 5.11 Representing classes in the 2D Arousal-Valence model.

By applying leave-one-trial-out method, we found that 43 out of 56 trials classified correctly while 13 classified incorrectly, as shown in Figure 5.12, i.e. 76.8% of all trials classified correctly. It is the same result got from using PSD. Therefore, the comparison between them is done in next section to selecting the best.

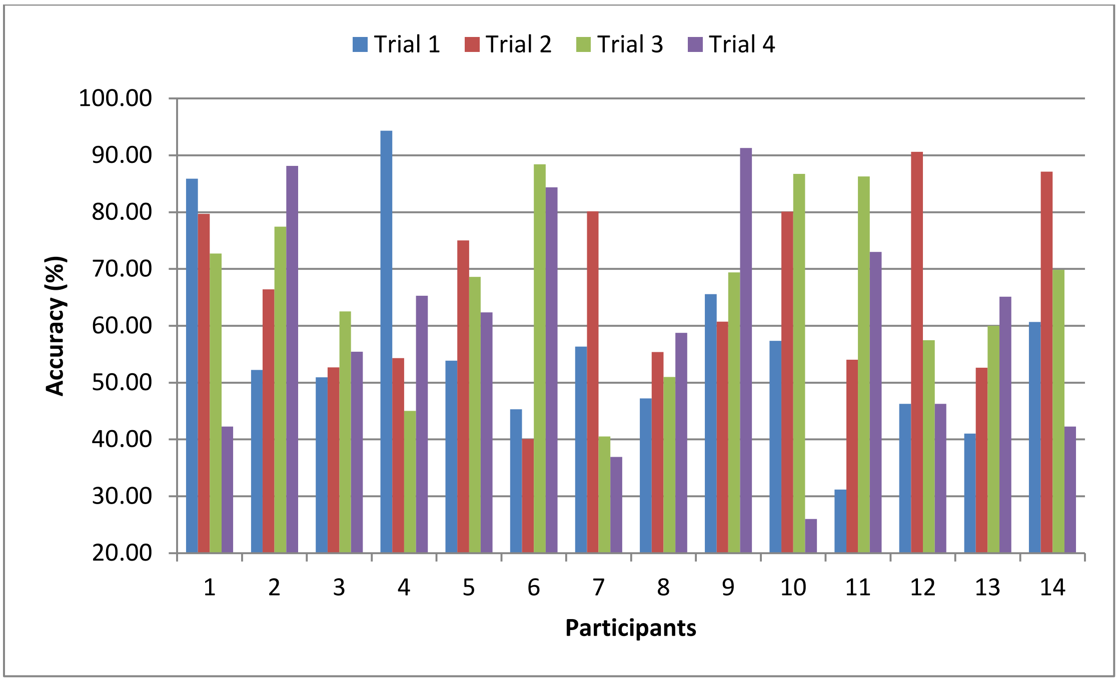


Figure 5.12 Accuracy to each trial using FD.

5.3 Comparing the Two Models

Both PSD model and FD model gave a good result, so the comparison between them are presented in Table 5.4 according to varied criteria to selecting the best model for those types of emotions. The first four criteria are calculated according to the following equations and Table 5.3:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5.1}$$

$$\text{Recall(True Positive Rate)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{5.2}$$

$$\text{Specificity(True Negative Rate)} = \frac{\text{TN}}{\text{FP} + \text{TN}} \quad 5.3$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad 5.4$$

TABLE 5.3 Confusion Matrix of PSD Model and FD Model.

class	**devout**	**non-devout**
devout (Positive)	1101 (TP)	95 (FP)
	11397 (TP)	902 (FP)
non-devout(Negative)	172 (FN)	1069 (TN)
	901 (FN)	12353 (TN)

* TP (True Positive), FP (False Positive), TN (True Negative), FN (False Negative).

PSD model   FD model

TABLE 5.4 The Comparison between The Two Models

Criteria	**PSD Model**	**FD Model**
Accuracy of 10 fold-cross validation	89.04%	92.94%
Precision	92%	92.67%
Recall	86.5%	92.67%
Specificity	91.84%	93.2%
Number of trials that classified correctly	43 out of 56	43 out of 56
Number of features	48 features	3 features
Number of used channels	12 channels	3 channels
Number of samples	2437	25553

Overlapping	No overlapping	90% overlapping
Execution time of processing signals and extract the features	26.85 seconds	126.688 seconds
Execution time of building the model	1.075 seconds	24.580 seconds
Suitable to run in real-time	yes	yes

As shown in Table 5.4, precision in both models is approximately the same which means the number of samples that are non-devout and classified devout in both models are very few. From recall and specificity, the recognition in FD model is higher than PSD model for devout and non-devout classes with the higher proportion for non-devout class. We can conclude that the corrected prediction for each class in both models is high which means most samples were classified correctly. Although FD model requires features and channels less than PSD model, the execution time of PSD model to processing signals, extract the features and build the model is significantly less than FD model. Use overlapping in FD model caused a delay in time and increasing in the number of samples which leads to more time to build the model. As we aim to develop BCI that runs in real-time, we selected PSD model to build that interface, next chapter explains it in details.

5.4 Comparing with Previous Work

In previous work [20], the researcher used all 90 trials, and the model has been built using FD feature that consists of arousal value from FC6 and valence values from AF3 and F4 channels. For each trial, he computed the average of all samples to become one sample per trial. As we mentioned already, the target emotion does not generate immediately which means some recorded seconds do not belong to it, so taking the average is not a good way to extracting the features. The proposed model achieved accuracy higher than the previous model. The advantages of proposed model that are not found in the previous model are:

- Classification of each second, enabling us to know the emotion of any second,
- There is no overlapping, which means the time required for extraction the features less than the previous model, thus, it runs faster in real-time.

Consequently, we can conclude that the proposed model has progressed on the previous model.

Chapter 6

Emotional Model in Real Time

The adopted model, as explained in the previous chapter, depended on PSD feature to frequency bands Gamma, Beta, Alpha, and Theta. It used 12 channels and SVM classifier. The previous model [20] was developed to system run in real time. That system was tested and worked successfully in terms of connecting with EMOTIV device, recording data, estimate the user's emotion, and showing the result in real time. Since this work aims to develop system runs in real time and has the same objectives of the previous system, we enhanced that system by replacing the model with our model to produce the new system. Figure 6.1 illustrates the worked mechanism of this system. The interface of this system shows in Figure 6.2. The user can select up to six verses and starts listening to them. EEG signal is recorded during the listening. The PSD feature is calculated from EEG signal for each verse using the same approach explained previously. The adopted model is used to estimate the class (emotion) of each verse based on PSD values; Figure 6.3 shows the flowchart of this model. The final emotion (devout or non-devout) is obtained by majority voting between the classes of all listened verses.

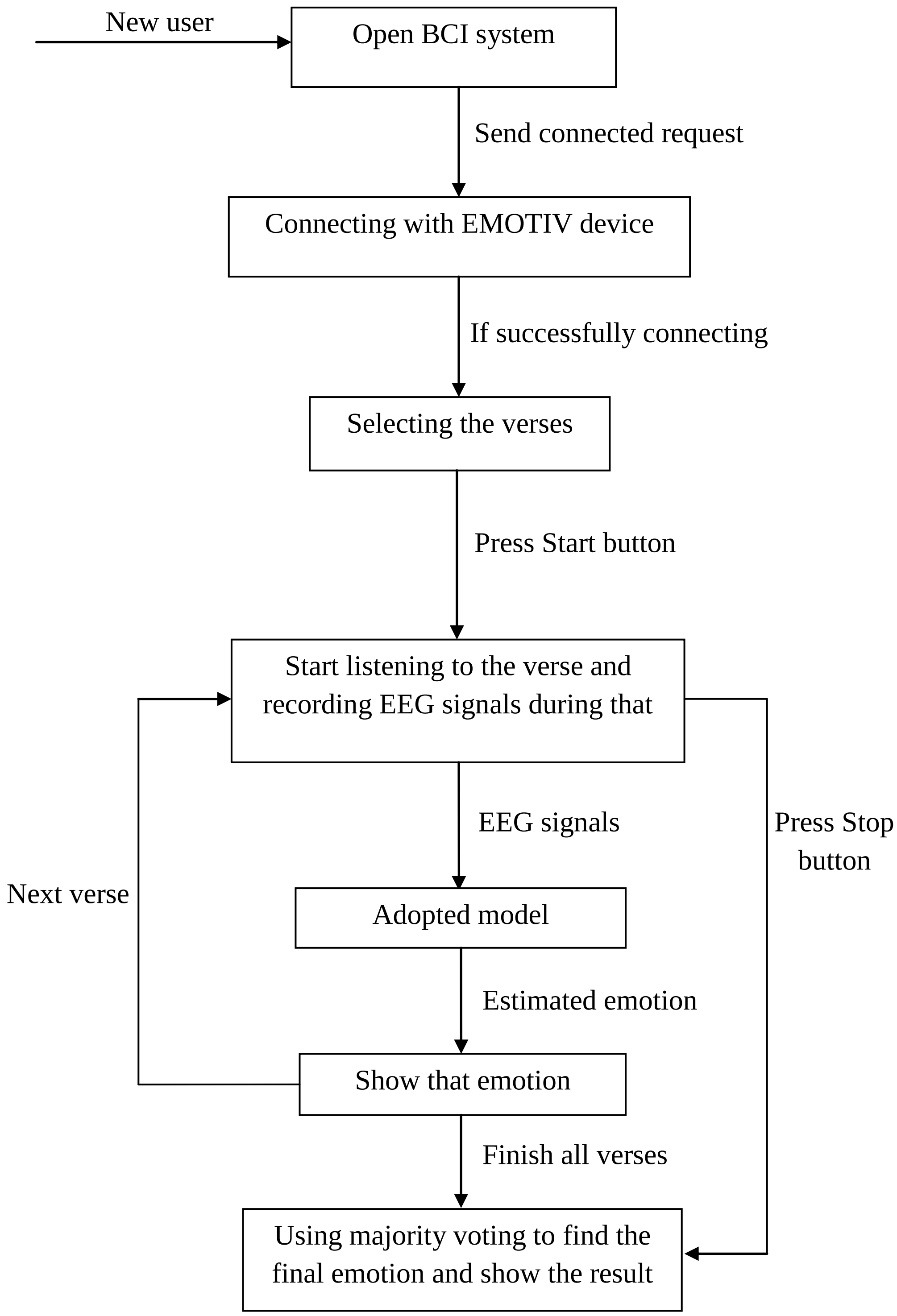


Figure 6.1 Mechanism of the proposed BCI system.

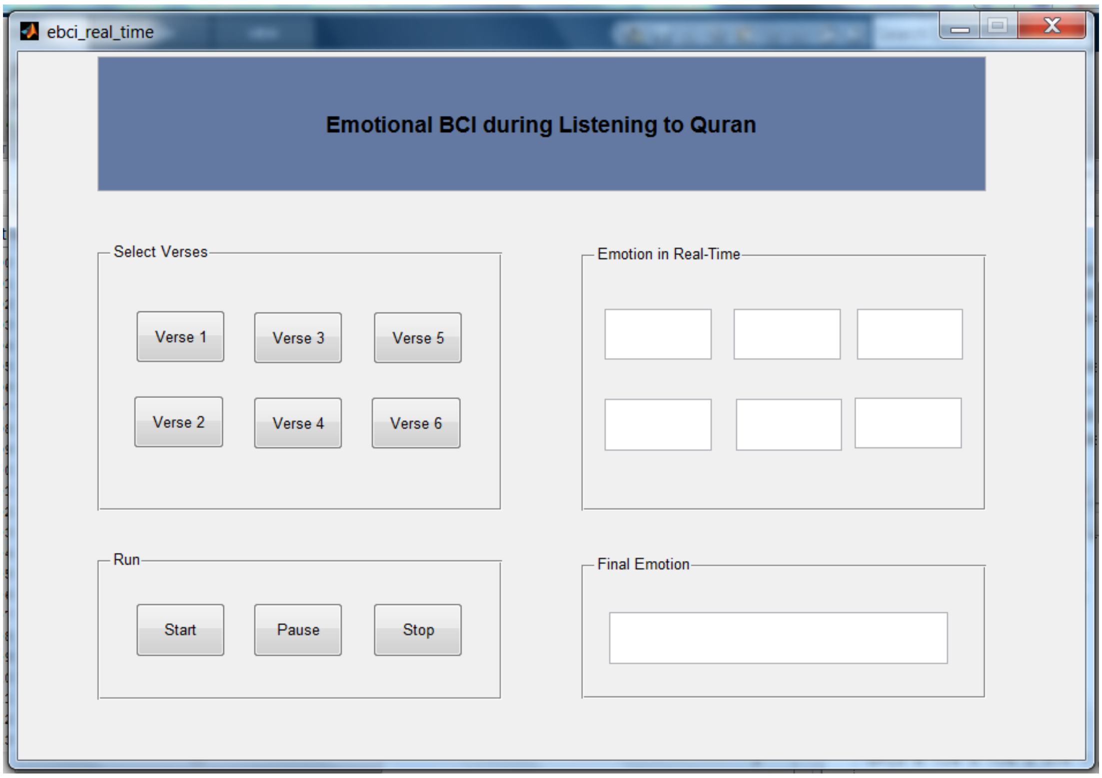


Figure 6.2 The interface of BCI system.

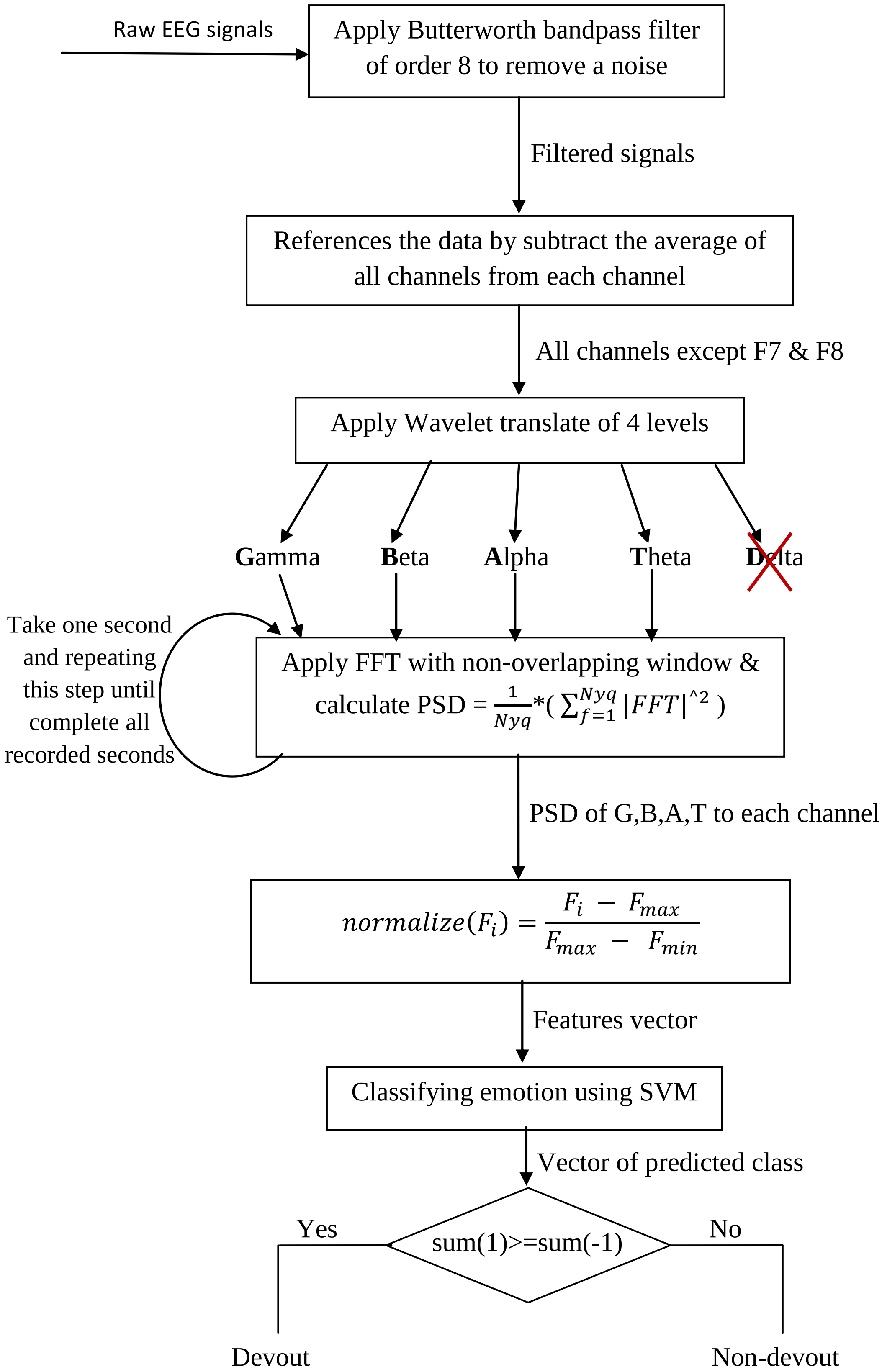


Figure 6.3 Flowchart of the adopted model.

Chapter 7

Conclusion and Future Work

7.1 Conclusion

We have proposed an emotional BCI system where the emotion of a user can be estimated during listening to Quran verses. Two types of emotions (devout and non-devout) were estimated. Two types of features (PSD and FD) were used to build independent models and a comparison between them according to many criteria was done to select the best one. The best model was adopted in this system.

The thesis's findings were as following:

- Electrodes T7 and T8 are the most suitable to calculate valence level when using FD method.
- Temporal and frontal lobes give a good accuracy comparing with the other lobes.
- High-frequency bands are better than low-frequency bands in identifying emotions.
- PSD feature is more suitable than FD when running the system in real time.

The difficulties were the none existing of labeled stimuli database for Quran audio clips like IADS and GAPED. Nevertheless, we achieved high accuracy at 89.04%., which outperformed the previous model.

7.2 Future Work

As a future work, the following points can be studied in more detail to improve the usability of the proposed system:

- Improve the accuracy of the proposed emotional system.
- Consider more emotional states in Emotional system.
- Use other stimuli such as pictures, or pictures with audio.

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واجهة حاسب دماغية عاطفية أثناء سماع القرآن

إعداد

مشاعل لفاي السلمي

بحث مقدم لنيل درجة الماجستير في العلوم

(الحاسبات وتقنية المعلومات)

إشراف

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كلية الحاسبات وتقنية المعلومات

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محرم ١٤٣٨ هـ / أكتوبر ٢٠١٦ م

واجهة حاسب دماغية عاطفية أثناء سماع القرآن

مشاعل لفاي السلمي

الملخـص

واجهة الحاسب الدماغية هي طريقة للتفاعل تسمح للمستخدم بالتفاعل مع العامل الخارجي باستخدام اشارات دماغه. من ناحية أخرى، تلعب العاطفة دوراً مهماً في حياتنا اليومية وتؤثر على قراراتنا. لفهم أفضل للسلوك الإنساني لابد من تقدير حالته العاطفية.

تم اقتراح طرق مختلفة لتقدير الحالة العاطفية للمستخدم. معظم هذه الطرق تعتمد على صوت المستخدم أو وجهه أو حركات جسمه والتي تكون غير موثوقة لأن المستخدم يمكنه إخفاء مشاعره. للتغلب على هذه المشكلة نقترح في هذا البحث نظاماً لتقدير الحالة العاطفية للمستخدم من إشارات دماغه والتي تعتبر أكثر موثوقية من الطرق الأخرى وتمكننا من معرفة الحالة العاطفية الداخلية للمستخدم. من أجل ذلك، تم تصميم تجربة تسمح للمستخدم بسماع آيات من القرآن الكريم بينما يتم تسجيل وتحليل إشارات دماغه وذلك بهدف تقدير حالته العاطفية.

تم تطبيق النموذج المقترح على ١٤ مستخدم وقد بينت النتائج التي حصلنا عليها أن النموذج المقترح يسمح بتقدير الحالة العاطفية للمستخدم بشكل صحيح بنسبة ٨٩,٠٤%. نحتاج لعمل تجارب إضافية لتقييم أداء النموذج المقترح في الزمن الحقيقي.