

國立交通大學

生醫工程研究所

碩 士 論 文

利用情感性視覺誘發腦磁波之情緒辨識

Emotion Recognition using Magnetoencephalographic
Recordings Evoked by Affective Visual Stimuli

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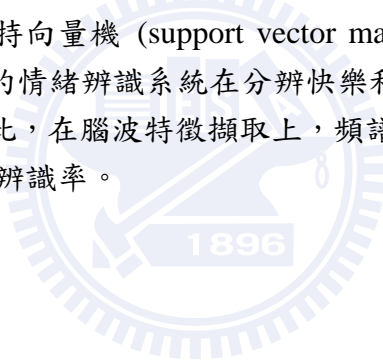
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摘要

近年來因為情緒和壓力造成的情感性疾病逐年增加，如能讓智慧型環境系統偵測我們的情緒，當偵測到負面情緒時，系統能夠適時的改變週遭的環境，如光線、溫度、音樂等，讓我們的情緒能因環境的舒適而改善，將有助於降低情感性疾病的發生。因此情緒的辨識系統變得越來越重要，關於情緒辨識的各方面研究也在近幾年內蓬勃發展。在情緒辨識的領域上，過去大都採用臉部表情、語音及肢體語言等外在表徵來辨識情緒，本研究提出一個基於腦磁波訊號的情緒辨識系統，採用情感性視覺刺激的誘發，觀察腦磁波訊號中所呈現出的腦波變化來進行情緒辨識。本情緒辨識系統分為生理訊號的擷取、特徵擷取、分類三個主要部份，本研究共收集 14 位正常人與 14 位憂鬱症患者，並使用五種特徵擷取方法，分別為事件相關磁場(event-related magnetic fields, ERF)、頻譜能量密度(power spectral density, PSD)、自迴歸模型(autoregressive (AR) model)、主成分分析(principal component analysis, PCA)、以及局部線性嵌入(locally linear embedding, LLE)，經比較這些特徵擷取方法後，我們採用結合頻譜能量密度的頻域特徵與局部線性嵌入的空間降維，並利用支持向量機 (support vector machine, SVM)來進行情緒分類。實驗結果顯示，我們的情緒辨識系統在分辨快樂和害怕這兩種情緒時，平均準確率能達到 91.8%。因此，在腦波特徵擷取上，頻譜能量密度與局部線性嵌入的結合，可以達到不錯的辨識率。



Abstract

The prevalence of affective disorders has been increasing recently. One possible remedy is to construct an intelligent environment system which can recognize emotions and adjust the conditions of environment like temperature, light, and music to comfort the subjects when their negative emotions are detected. Therefore, automated emotion recognition has attracted more and more attentions in the field of affective computation. In the literature, there have been many research works which recognize emotions through external manifestation, such as facial expression, voice, and gestures. In this works, we propose an emotion recognition system using magnetoencephalographic (MEG) signals evoked by affective visual stimuli. Our system can be divided into three parts including physiological signal acquisition, feature extraction, and classification. We recruited 14 normal subjects and 14 bipolar disorder patients. Five kinds of feature extraction methods were evaluated in this work, including: event-related magnetic fields (ERF), power spectral density (PSD), autoregressive (AR) model, principal component analysis (PCA), and locally linear embedding (LLE). We adopted the features and the combination of PSD and LLE as use support vector machine (SVM) to categorize happy and fear emotions. According to our experiments, the proposed system can achieve 91.8% accuracy of emotion recognition.

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Hsin-Fang Lee



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Chapter 1

Introduction



In this chapter we briefly introduce background knowledge of the thesis. In Section 1.1, we first briefly introduce the motivation of this study and survey the research works related to emotion recognition. Then Section 1.2 presents thesis scope. Finally Section 1.3 presents the thesis organization.

1.1 Motivation

What is emotion? Emotion is a complex physiological process and a psychological phenomenon. When a subject is exposed to physical or mental stimulation, the external stimulation will lead to all sorts of psychological reactions, which is called emotion. In our daily lives, emotions play a powerful and significant role in social network which can help people to understand others' feelings. According to medical research findings, emotion is an important relationship to the disorders in psychopathology, the survey based on the International Statistical Classification of Diseases and Related Health Problems 10th Revision (ICD-10) classification found this there are around 15% at population to suffering affective disorders [29]. Furthermore, affective disorder has been identified as century one of the three major diseases in the twenty-first. According to the World Health Organization survey (WHO) [29], affective disorders patients have been increasing, and resulting in serious social problems. Affective disorder is an accumulation of negative emotions in life. How to reduce the prevalence of depressive disorders is very important.

This is a very useful information for the application of intelligent environment from the emotion recognition. Recently construction and application of intelligent environments becomes a prosperous research field. The intelligent environment research aims to use information technology tools, that is to say, the application of intelligent environment research is to create a more friendly environment for real-world environment to increase perception and wisdom, the environment can take the initiative in service human. For example, when the system detection of negative emotions is increasingly from human, the system can timely adjust the environment temperature or light, because the comfortable environment that human positive emotion is increasingly.

In the emotion recognition field, most previous studies have focused on the facial ex-

pressions, voice and physiological signals. In the literature, there have been many research works which recognize emotions through external manifestation, such as facial expressions, voice and gestures, besides there can be observed the emotion expression, the signal also will often accompanied by physiological changes. In many of the emotion response, specific features of human facial expression, moreover often complex and diverse. We were to determine their expression via the change of facial features location. However, face detection and video were based on external manifestation, but not necessarily representative of their true inner feelings. In physiology, we realize that when emotional aroused, we cannot self-control of physiological response signal. Therefore, physiological signal is a very effective indicator.

Recognition the emotions from physiological signal can be achieved by several ways such as Electrocardiogram (ECG), Electromyogram (EMG), Blood volume pulse (BVP), Electrodermal activity (EDA, SC, GSR), Skin temperature (SKT), Respiration (RESP), Electroencephalography (EEG), and Magnetoencephalography (MEG), as shown in Figure 1.1.

The human physiology signals, modern medicine has confirmed that the brain's various activities, including thoughts, emotions, desires and so on, the relationship between electrical current and chemical reactions of tend to come out, we can estimate use of the brain waveform. Therefore, in this study we propose an emotion recognition system based on brain signals.

1.2 Thesis scope

The objective of this thesis is to recognize emotion from the healthy by the MEG signals. We preprocess the MEG signals and then extract feature, there are five kind of features. The first is the event-related magnetic fields (ERF) feature which extract from the latency and amplitude, the second is power spectral density (PSD) feature which extract from the power spectral density, the third is autoregressive (AR) model feature which extract from the AR coefficients, the fourth is principal component analysis (PCA) feature which extract from the principal components, and the other one is locally linear embedding

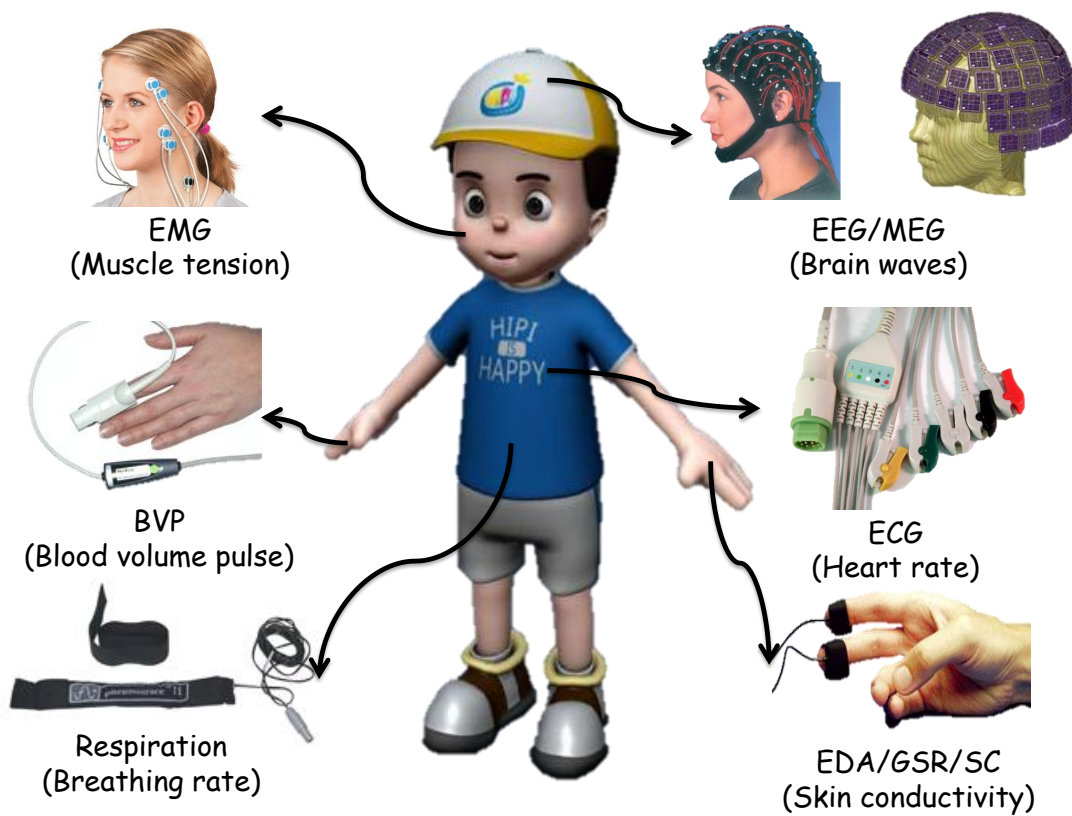


Figure 1.1: Physiological signals-based emotion recognition.

(LLE), the feature of low dimensionality representation of dimensionality reduction from spatial. Finally, those features are used to differentiate the emotion by classification.

1.3 Thesis organization

In the following chapters, we will bring up the proposed methods, experiment results and some discussion in this work. The feature extract and classification procedure method will be introduced in Chapter 3, the classification results in Chapter 4. Then, we will have some discussion and conclusions in Chapter 5 and Chapter 6.





Chapter 2

Related works



Over the years, related to the study of the emotion recognition based on physiological signals, there have been many experts and scholars in the study, there are many methods have been proposed. The research about emotion recognition using physiological signals divided to two categories, autonomic nervous system and central nervous systems.

2.1 Emotion psychology

2.1.1 The definition of emotion

Daniel Goleman [4] defines the emotion as "feeling, the idea of a specific, physiological state, psychological state, and related behavioral tendencies". That is, the emotion consists of three parts: personal feelings, thoughts, and behavior, when the three parts are in equilibrium, is that mental health.

The general ways of emotion evoked by visual and auditory involve the same basic circuit, both activated by the mirror neurons. The brain's mirror neuron system observes how other people act to understand their intentions and then produces compassion. Neuroscientists believe that the general observation and action system provides a neural mechanism which enable others' to automatically understand others' behavior, intentions and emotions. [20].

2.1.2 The theory of emotion

James-Lange theory of emotion

The American psychologist James (1884) and Lange (1885) was first proposed to explain the emotion of psychologist. They believe that emotions are caused by physiological changes, rather than stimulation [10].

Event \implies arousal \implies interpretation \implies emotion

Gannon-Bard theory of emotion

The American physiologist Cannon and his student Bard, they believe that cannot explain that only physiological responses to emotions, emotions and physiological changes should be simultaneously generated [3].

Event \implies simultaneous arousal and emotion

Schachter-Singer theory of emotion

Schachter-Singer theory of emotion is also called two-factor theory of emotion, because they believe that emotions are produced have two factors: (1) physiological responses, and (2) cognitive assessment [24].

Event \implies arousal \implies reasoning \implies emotion

2.1.3 The category of emotion

Before we proceed to the recognition of emotion, we must first understand how the classification of emotions, but there has not been consensus on the emotion classification, therefore, many researchers have put forward various regarding emotional classification. Although there are different categorization methods of emotions, but the emotion categories are basically the same. Some often refer to the emotion classification model as Plutchik's [19] three-dimensional emotion model, as shown in Figure 2.1. Russell's [22] two-dimensional emotion mode, as shown in Figure 2.2, and Thayer's [27] two-dimensional emotion mode, as shown in Figure 2.3.

In the Plutchik's three-dimensional emotion mode, which the cones vertical dimension represents intensity, and the circle represents degrees of similarity among the emotions [18]. The eight sectors are designed to indicate that there are eight primary emotion dimensions defined by the theory arranged as four pairs of opposites. In the exploded model the emotions in the blank spaces are the primary dyadsemotions that are mixtures of two of the primary emotions. The Russell's two-dimensional emotion mode of affect with the horizontal axis representing the valence dimension and the vertical axis representing the arousal or activation dimension [25]. The Thayer's two-dimensional emotion mode, which can be divided into four quadrants with four emotion [27].

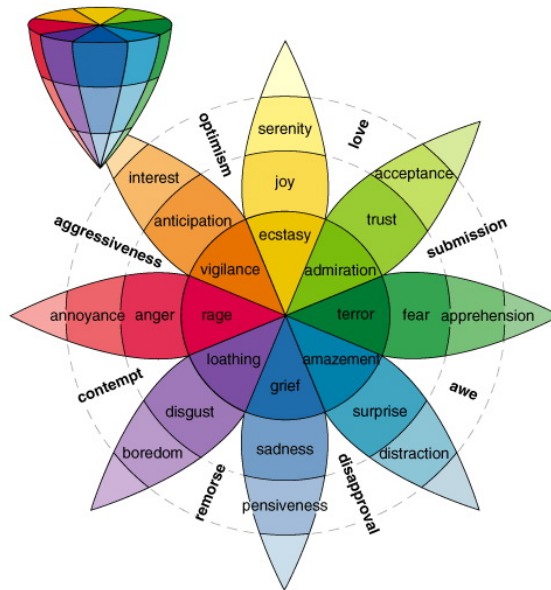


Figure 2.1: Plutchik's three-dimensional emotion mode [25].

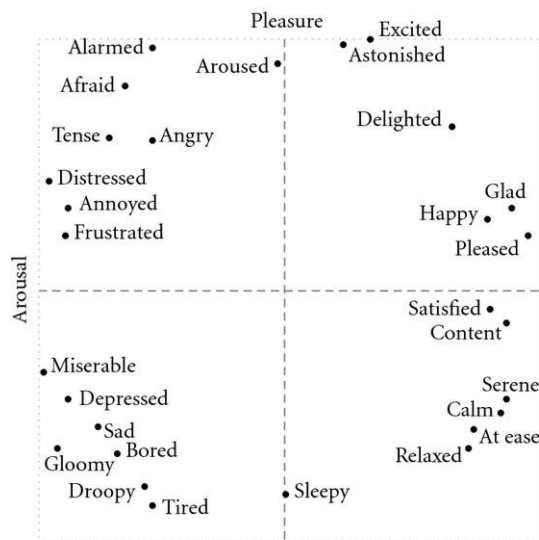


Figure 2.2: Russell's two-dimensional emotion mode [25].

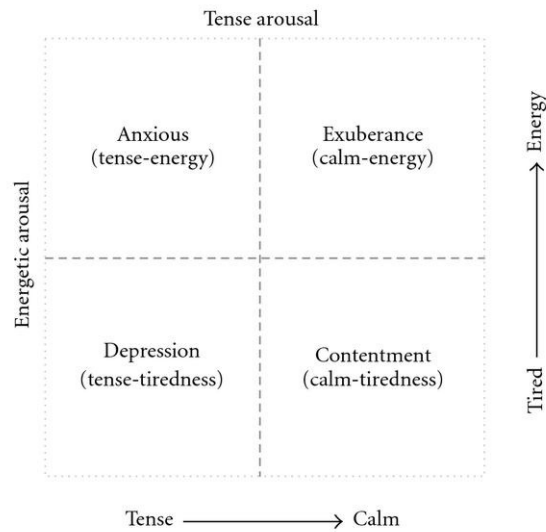


Figure 2.3: Thayer's two-dimensional emotion mode [25].

In this study, we adopt 2-D model of the two emotion are fear and happy on behalf of positive and negative emotions and high arousal.

2.2 Physiological signals

2.2.1 Autonomic nervous system and peripheral nervous system

Emotion-specific activity in the autonomic nervous system was generated by constructing facial prototypes of emotion muscle by muscle and by reliving past emotional experiences. The autonomic activity produced distinguished not only between positive and negative emotions, but also among negative emotions [6].

Blood volume pulse (BVP)

BVP is a measurement of the blood flow, previous studies pointed out that human produce excitement, tension, anger, feel a stress and to greater emotional response, that will increase blood flow; but relaxed, calm, and sad, that will reduced blood flow. Therefore, the subjects' emotion response is through changes in blood flow to detect, blood flow measured

usually by the fingertip.

Electrocardiogram (ECG)

ECG is a measurement of contractile activity of the heart. Previous studies pointed out that in a relaxed, happy, and calm state, heart rate will decrease; in the excitement, tension, and pressure state, heart rate will increase.

Electromyogram (EMG)

EMG is a measurement of muscle activity or frequency of muscle tension, previous studies pointed out that human in the tense state, the EMG rate will increase, but in the state of relaxation, EMG rate will decrease.

Respiration (RESP)

RESP is a measurement of the frequency to breathing, when the lungs inhale air to make the chest expand; the exhalation of air, chest compressed air by discharges, chest will become smaller. The breathing is the same as heart rate, that have a regular cycle, so the change through the respiratory rate, can be observed emotional changes of subjects as well. Previous studies pointed out that human be excited, nervous, and angry, the breathing rate will increase; be relaxed, calm, pleasant, the breathing rate will decrease.

Skin conductivity (SC, GSR, or EDA)

EDA is a measurement of the skin ability to conduct electricity. Previous studies pointed out that skin conductivity and the degree of emotional arousal are linearly related. The emotion generates by induced while, that will to enhance the effect of the sympathetic nervous, so the surface of the skin secretion of sweat glands, skin humidity changes, increase in the subject's skin conductivity, cause dramatic changes in GSR signals. Therefore, when people the tension, excitement, and fear, the skin conductivity higher.

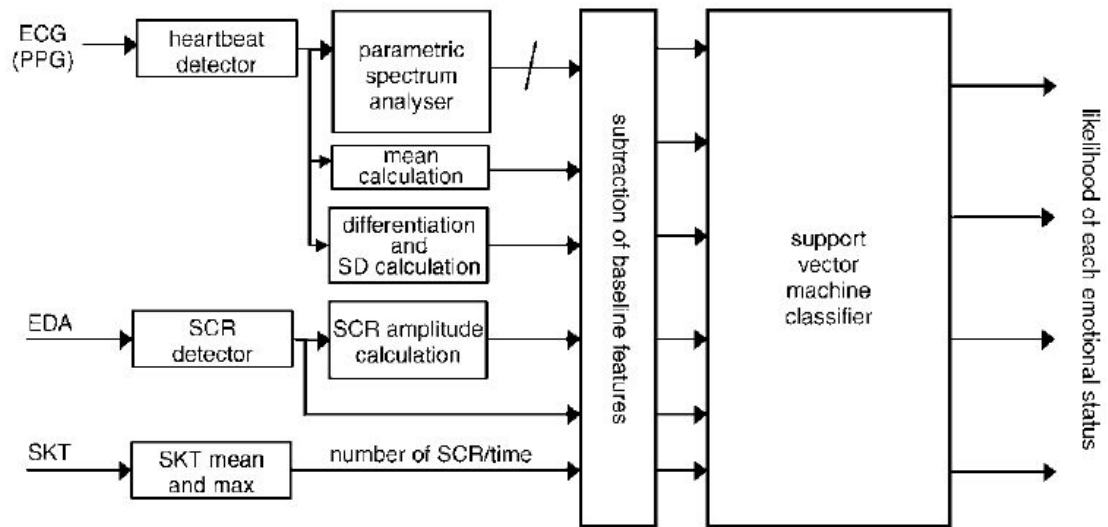


Figure 2.4: Kim, K. H et al. development of emotion recognition system [13].

Kim et al., [13] experimented with emotion recognition. Kim, K. H. using voice, video and picture as stimuli to induce four emotions. The four emotions are sadness, anger, stress, and surprise emotions. They using three physiological signals are collected: ECG, EDA, and SKT, will be to collect the physiological signals of the feature extraction, and using support vector machine for classification of the data, as shown in Figure 2.4.

Andre et al., [12], research and development of a scheme of emotion recognition. The experiment the main stimulus is music, using music to stimulate the subjects of real emotional state. The use of four-channel physiological signal sensors (biosensors): ECG, EMG, SC, and RSP respectively. Using an extended linear discriminant analysis (pLDA) classified four kinds of musical emotions: positive/high arousal, negative/high arousal, negative/low arousal, and positive/low arousal, as shown in Figure 2.5. The recognition accuracy was 95% and 70% for subject-dependent and subject-independent classification

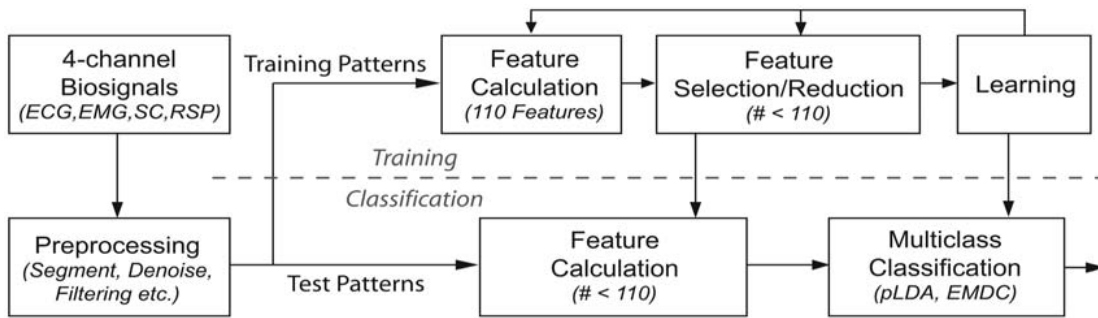


Figure 2.5: Kim, J. and Andre, E. development of supervised statistical classification system for emotion recognition [12]

2.2.2 Central nervous system

In addition to periphery biosignals, signals captured from the brain in central nervous system (CNS) have been proved to provide informative characteristics in responses to the emotional states. CNS has been used in cognitive neuroscience to investigate the regulation and processing of emotion for the past decades [2] [5]. The related references indicate that the visual processing in the brain is within 100ms followed by 100ms of emotion processing. After 200ms there can be behavior phenomenon involved in the neuron network activities. [1] [17] [26].

Power spectra of the EEG were often assessed in several distinct frequency bands, such as delta ($\delta : 1 - 3Hz$), theta ($\theta : 4 - 7Hz$), alpha ($\alpha : 8 - 13Hz$), beta ($\beta : 14 - 30Hz$), and gamma ($\gamma : 31 - 50Hz$), to examine their relationship with the emotion states [9] [15] [16].

Magnetoencephalography (MEG)

MEG is a measurement of magnetic fields produced by the ensemble of neuronal activities inside brain.

Electroencephalography (EEG)

EEG is a measurement of the electrical activity of the brain.

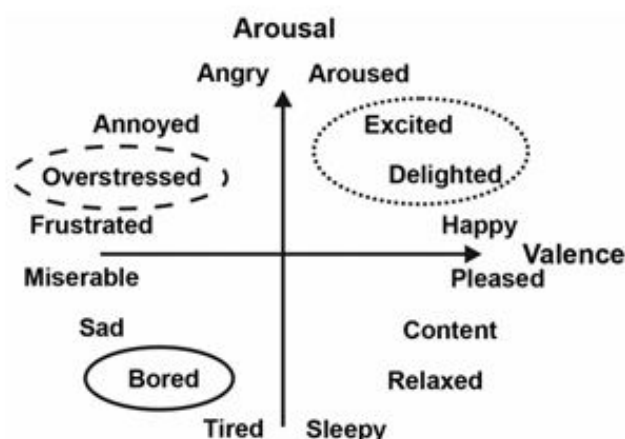


Figure 2.6: The 2-D emotional space [14].

Frantzidis et al., [7] proposes a methodology use for EEG signals for emotion recognition, the system the main stimulus is IAPS collection in which picture, classification of four emotional states HVHA (high valence and highly arousal), HVLA (high valence and low arousal), LVHA (low valence and highly arousal), LVLA (low valence and low arousal) is performed by a Cartesian 2-D emotional space, as depicted in Figure 2.6. The achieved overall classification rates were 79.5% and 81.3 % for the MD and SVM.

Jung et al., [11] proposes EEG-based emotion recognition system, the system the main stimulus is music, use music to stimulate the subjects emotional, classification of four emotional states: joy, anger, sadness, and pleasure, and obtained an averaged classification accuracy of $82.29\% \pm 3.06\%$.

2.3 Feature extraction

In research on brain wave about emotion recognition, researchers majority using feature extraction methods. The detection of the characteristic waveform use event-related potential and spectral power changes, extraction of useful information feature for classification. The event-related potential was averaged ERPs extracted from each channels, therefore,

amplitude and latency feature were extracted for the P100, N100, P200, N200, and P300 [7].

The power spectra were calculated using short-time Fourier transform (STFT) or fast Fourier transform (FFT), the resultant spectral time series was averaged into five frequency bands, delta ($\delta : 1 - 3Hz$), theta ($\theta : 4 - 7Hz$), alpha ($\alpha : 8 - 13Hz$), beta ($\beta : 14 - 30Hz$), and gamma ($\gamma : 31 - 50Hz$). The frequency and the corresponding with energy and the corresponding were used as features in the classification [7] [28] [9].



Chapter 3

Classification of affective evoked brain activities



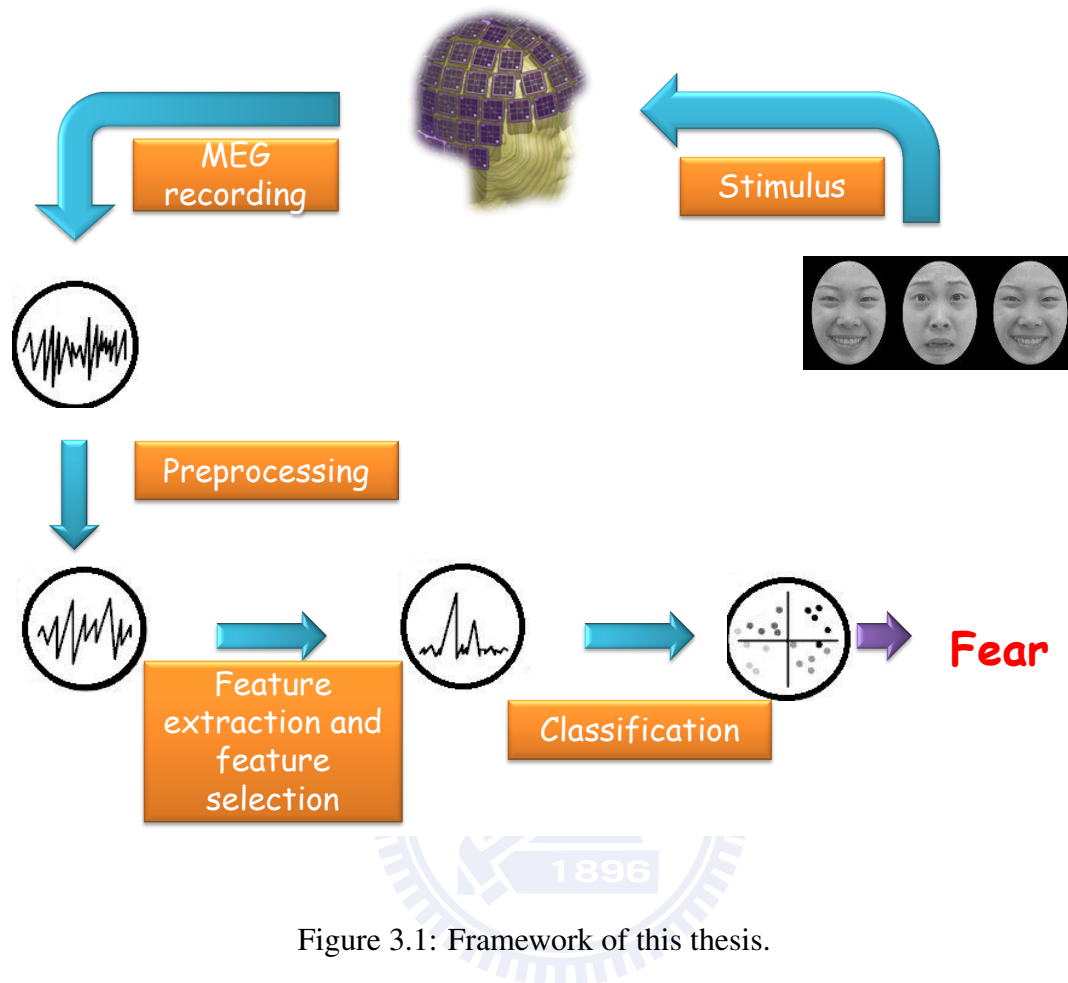


Figure 3.1: Framework of this thesis.

In this chapter, we describe the experiment procedure. We first introduce the materials used in the experiment, and then introduce the methods of experiment, which can be split into three main steps: (1) feature extraction, (2) feature selection, and (3) classification.

The emotion recognition system as shown in Figure 3.1. In this study, the system can be divided into five parts: signal acquisition, signal pre-processing, feature extraction, feature selection, and classification. In addition to frequency domain analysis, we also used to retrieve from the MEG waveform feature, predictive model to assess, linear dimension reduction, as well as non-linear dimension reduction to extract features, hoping to find the most representative and really to represent the emotional feature.

3.1 Materials

3.1.1 Participants

In this work, participants were 14 healthy (9 females and 5 males; ages between 30-55 years, mean 39.43 ± 9.02 years), and 14 bipolar disorder (BD) patients (11 females and 3 males; ages between 25-62 years, mean 41.71 ± 10.62 years), all right-handed. Experimental design and data collection were performed by Taipei Veterans General Hospital. The main contribution of this study is the analysis of the MEG signals. Demographic data of all participant as shown in Table 3.1.

Table 3.1: Demographic data of all participant.

	Normal (NC)	Bipolar Disorder(BD)
Participant, n	14	14
Gender (male/female), n	5/9	3/11
Age (mean age), mean SD	39.43 ± 9.02	41.71 ± 10.62
Handedness (right), n	14	14

3.1.2 Experimental paradigm

Affective visual stimuli consist of face images with two different emotions which are fear and happy. In this experiment, the participants are placed in a magnetic shielded room and are presented with the visual stimuli, and the brainwave signals induced by the stimuli are recorded by the MEG device. The task is to confirm that the participants can correctly recognize the emotion expressed. Participants can press the button while recognizing the presented face image is fear or happy. Each stimulus is displayed for 700 ms, and then a

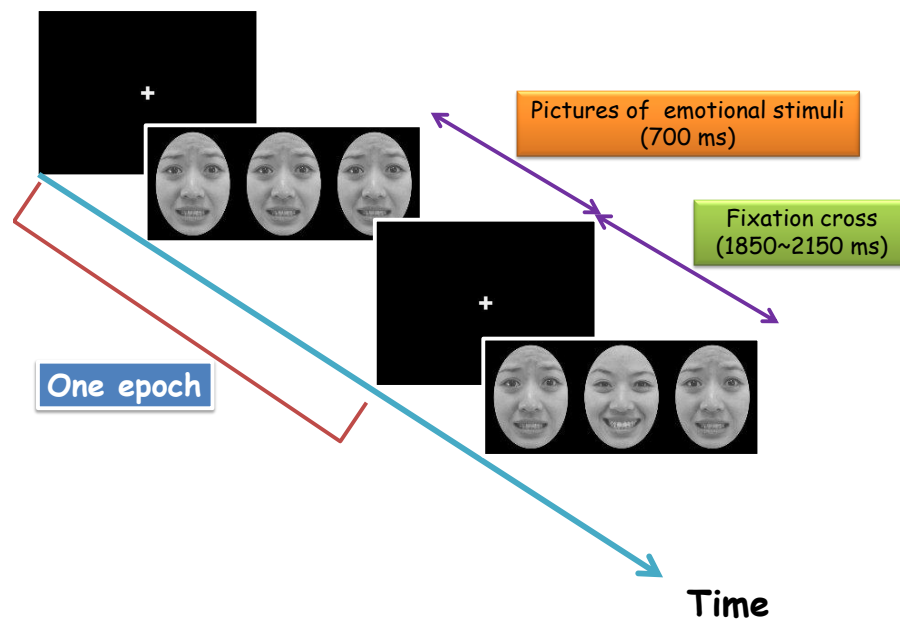


Figure 3.2: The experiment paradigm of emotion recognition.

fixation cross appears for a random time length ranging from 1850 ms to 2150 ms. The whole experiment paradigm is shown in Figure 3.2.

3.1.3 MEG device

MEG system is used for recording of the minute magnetic field generated by human brains electrical activity within the living human brain. The measurement was acquired by a whole-head 306-channel Neuromag Vectorview system (Elekta Neuromag Vectorview, Finland) which located inside a magnetically shielded room (Euroshield, Eura, Finland) at Integrated Brain Research Unit of Taipei Veterans General Hospital. The MEG system has 306 channels contains 102 magnetometers, 204 planar gradiometers 24 bits analog to digital conversion and up-to-8 kHz sampling rate which is sufficient to probe the fast variation inside human brain. The MEG device is shown in Figure 3.3.



Figure 3.3: The MEG device in Taipei Veterans General Hospital.

3.1.4 Neurophysiological recordings

MEG signals were recorded by a whole-head 306-channel Neuromag Vectorview system which located inside a magnetically shielded room at Integrated Brain Research Unit of Taipei Veterans General Hospital. The signals were recorded participants emotion state. The sampling rate was set at 1001.6 Hz and band-pass filtered was 0.03-330 Hz.

3.1.5 Data preprocessing

The brain signal relative to environmental interference noises is comparatively small. Hence we were to enhance the signal-to-noise ratio (SNR). The MEG signals were offline preprocessed as shown in Figure 3.4: (1) eliminate bad channels which has abnormal record, (2) the rejection of ocular artifact-contaminated trials, leaving only the segments without ocular artifacts-contaminated trials to accepted for further analysis, (3) signal space projection (SSP) was exploited to eliminate the unbalanced noise effect, (4) we use band-pass filter to exclude those unavoidable artifacts, and the signals were hardware band-pass filtering between 2 and 35 Hz, (5) we conduct the baseline correction by subtracting a baseline from the recordings. The baseline is usually estimated by the mean of in the 300 ms prior to stimulus, at which it the recordings are unaffected by the stimulus.

3.2 Feature extraction (feature generation)

3.2.1 Event-related magnetic fields

Event-related magnetic fields (ERF) is a measurement of neuronal activity patterns associated with the perceptual and cognitive processes occurring in the brain response to stimuli, that evoke a specific waveforms by the peak amplitude and latency.

We used ERF analysis of MEG recordings of emotion with fear and happy, stimuli is based on FgoHnogo and HgoFnogo tasks. The 200 ms for each participant, channels and emotion states, and each component is according to its latency and amplitude as shown in Figure 3.5, 3.6. Therefore, amplitude and latency feature are extracted for ERF components.

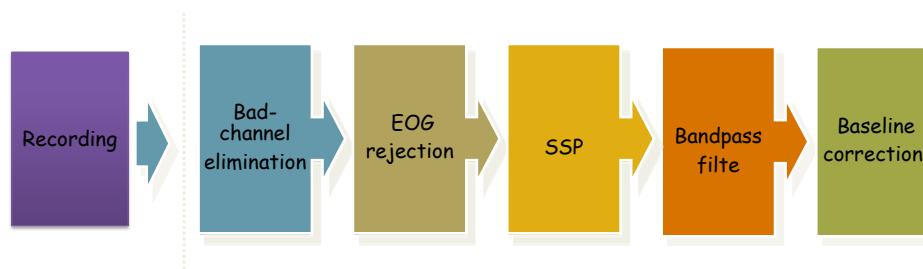


Figure 3.4: Preprocessing procedures for MEG.

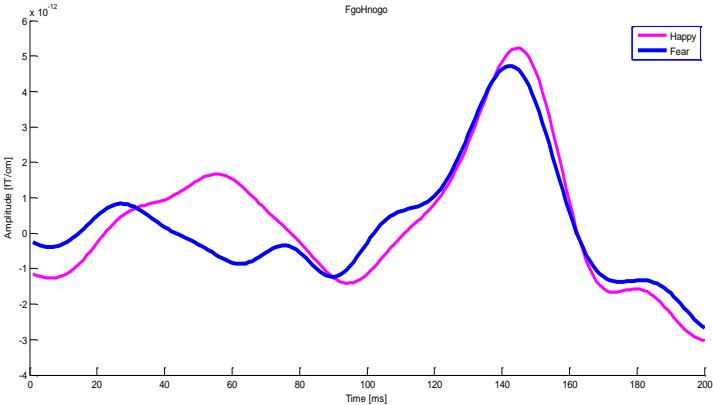


Figure 3.5: Waveforms of mean ERF regional amplitudes evoked by FgoHnogo condition.

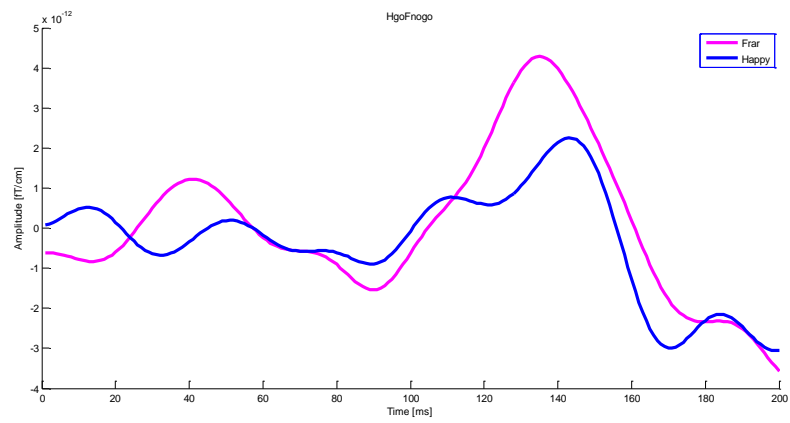


Figure 3.6: Waveforms of mean ERF regional amplitudes evoked by HgoFnogo condition.

3.2.2 Power spectral density

Powers of different frequency bands are one of the most commonly used features in the frequency domain analysis. First, MEG signals are transformed from time domain to frequency domain using fast Fourier transform (FFT) method. The spectrum of MEG signals is then further divided into four frequency bands, which are delta band ($\delta : 2-4Hz$), theta band ($\theta : 4 - 8Hz$), alpha band ($\alpha : 8 - 13Hz$), and beta band ($\beta : 13 - 30Hz$)(as show in Table 3.2). The power of these four frequency bands are then used as the features for analysis [7].

Table 3.2: Four frequency bands with frequency range respectively.

Frequency Band	Range (Hz)
delta band δ	2-4
theta band θ	4-8
alpha band α	8-13
beta band β	13-30

$$X(k) = \sum_{n=0}^{N-1} x(n)W_N^{kn}, 0 \leq k \leq N - 1 \quad (3.1)$$

Where $W_N = \exp \frac{-j2\pi}{N}$ and $N = \text{length}[x(n)]$.

3.2.3 Autoregressive model

Autoregressive (AR) model is one of the common linear forecasting model, the model prediction the data in the next time interval is based on the correlation between the variables and time series. It is commonly used in filed statistics and signal processing.

The AR model is defined by the equation:

$$x_i(t) = \sum_{n=1}^p a_i(n)x_i(t-n) + \varepsilon_i(t), n = 1, 2, \dots, p \quad (3.2)$$

The observed MEG signal can be written as by $x_i(t), i = 1, 2, \dots, n, t = 1, 2, \dots, T$, where i is the index of the MEG channels and t is the time point, p is the model order, $a_i(n)$ is the AR model coefficients, $x_i(t-n)$ is the data before time t , and $\varepsilon_i(t)$ denotes the noise.

3.2.4 Principal component analysis

Principal Component Analysis (PCA) is one of the common methods for feature extraction and dimensionality reduction. The PCA objective is to reduce high dimensional data set so we can use less number of interrelated variables and retaining as possible as much of variations in data set. Generally, high-dimensional data will consume more time to perform computing or classifying, therefore PCA method is to do a group of dimension reduction, and use fewer low dimensional data to represent a large group of data. In this research, we used PCA to reduce the MEG temporal signals as feature. Through PCA method, we can easily project the MEG temporal signals from 200-dimension to lower dimension space. The steps of PCA method are as following:

Step 1: Calculate the mean vectors

$$m = \frac{1}{nTr} \sum_{i=1}^{nTr} x_i \quad (3.3)$$

Where $x_i = [x_1, x_2, \dots, x_n]^T$ is $n - dimensionality$ MEG signals training data, nTr is number of the training data.

Step 2: Calculate the scatter matrix of the feature vectors

$$S = \sum_{i=1}^{nTr} (x_i - m)(x_i - m)^T = xx^T \quad (3.4)$$

Where S is $n * n$ matrix.

Step 3: Calculate the eigenvectors of the scatter matrix (principal axes)

$$e^T S e = \lambda \quad (3.5)$$

Step 4: Calculate the projected feature vectors (principal components)

$$y_i = A^T(x_i - m), \text{ where } A = [e_1, e_2, \dots, e_d] \quad (3.6)$$

Where A is $n * d$ matrix, consist of the eigenvectors, $y_i = [y_1, y_2, \dots, y_d]^T$ is the PCA feature vectors.

3.2.5 Locally linear embedding

The problem of dimensionality reduction applications in many fields of machine learning, pattern recognition, data compression, and neural computation etc. Here we describe Locally Linear Embedding (LLE), LLE is a nonlinear dimension reduction method that it can project high dimensional data to a lower-dimensional manifold. In the dimension reduction process, every point will retain the relationship with the original point, these neighboring points will not change with any displacement or rotation as illustrated in Figure 3.7.

The LLE algorithm there are three main steps as shown in Figure 3.8. The algorithm is summarized in the following three steps [8]:

Step 1: For each point $x_i = 1, 2, \dots, n$, search for its nearest neighbors.

Step 2: Compute the weights $W(i, j), i, j = 1, 2, n$, the best reconstruct each point x_i , from its nearest neighbors, so that to minimize the cost.

$$\varepsilon(W) = \sum_{i=1}^n \left\| x_i - \sum_{j=1}^n W(i, j)x_{ij} \right\|^2 \quad (3.7)$$

Where, x_{ij} is the j th neighbor of the i th point. The weights cost function to satisfy two constraints: (1) Only can used the neighbor at each point x_i to reconstructed, $W(i, j) = 0$, if x_j does not neighbors of x_i .

$$\sum_{j=1}^n W(i, j) = 1 \quad (3.8)$$

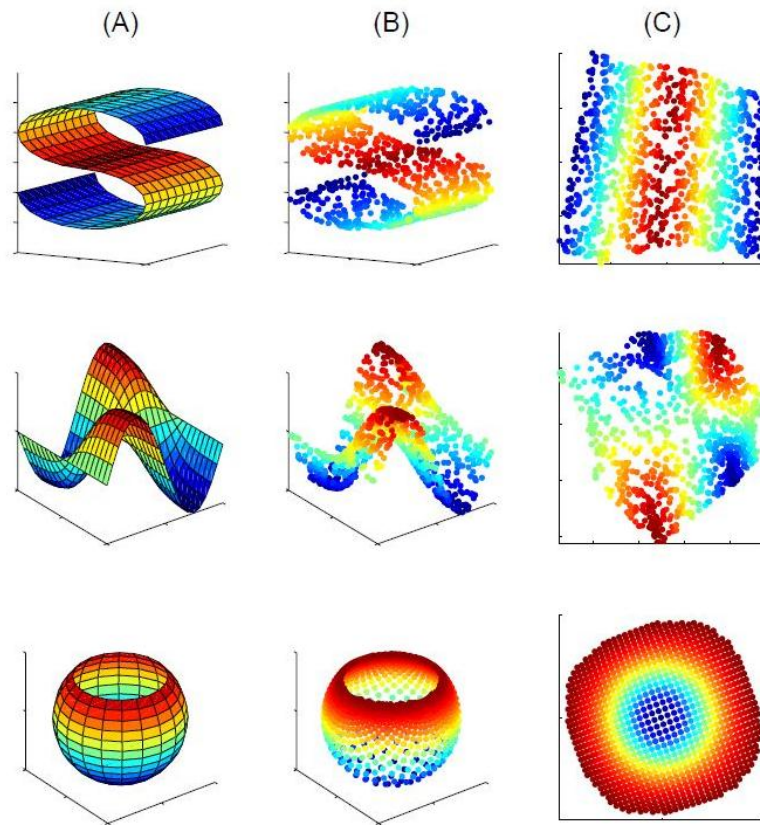


Figure 3.7: The example of nonlinear dimensionality reduction as illustrated for data (B) sampled from a two dimensional manifold (A). By way of nonlinear dimensionality reduction algorithm (LLE), the data is mapped to two-dimensional space (C) [23].

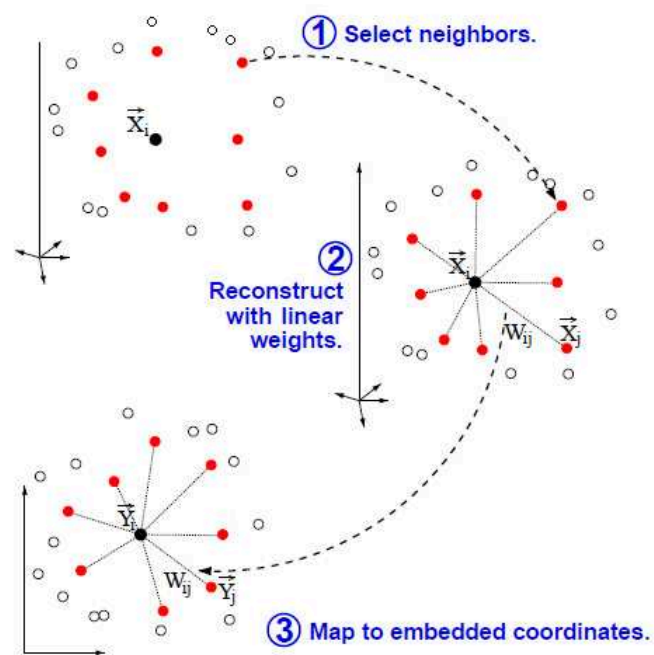


Figure 3.8: Steps of locally linear embedding [21].

Step 3: Use the weights previous step to compute the corresponding points $y_i, i = 1, 2, \dots, n$, so that to minimize the cost function to find a new d -dimensional coordinates y_i .

$$\Phi(y) = \sum_{i=1}^n \left\| y_i - \sum_j W(i, j)y_j \right\|^2 \quad (3.9)$$

Summing up the above five methods at parameter set. The parameter set for each method as shown in Table 3.3.

Table 3.3: The parameter set for each method.

Methods	parameter set
AR model	15
PCA	Number of sorted eigenvalues with 95% of accumulated values
LLE	20

3.3 Selected features

The goal of feature selection is to select the most influential features from the original feature that recognition rates can reach the maximum value. Through the process of feature selection, we can achieve accuracy.

We select the features PSD that have the highest recognition rate to be combined with LLE. Use PSD method to extract temporal information and then use LLE method to extract spatial features..

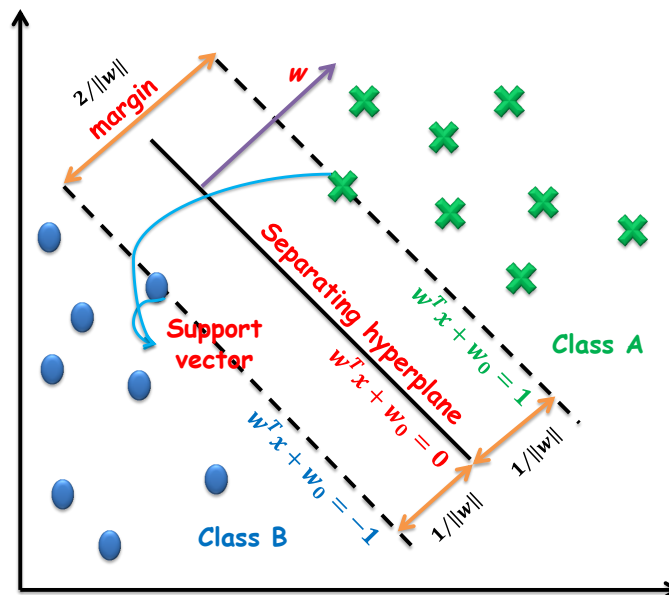


Figure 3.9: SVM classifier. There are two different data and we need to find a decision boundary to separate two classes of data and the margin between the two is maximal.

3.4 Classification

3.4.1 Support vector machine

In this work, we use support vector machine (SVM) to classify the emotion state for each MEG segment.

SVM is a statistical-based theory which is supervised learning method used for classification and regression analysis. In recent years, it has been widely used in pattern recognition and data classification. Also because of its high accuracy and great ability to deal with a large number of predictors, it often use in biomedical.

The main idea of SVM is to determine a hyperplane which can separate different classes from all samples, and allow maximal margins between the training data and decision boundary as shown in Figure 3.9 illustrate the classifier of SVM.

The goal of SVM is to find a best hyper plane that can separate different class of group

from all data. Assume there is a space data R^d , it has N different classes of sample. Then the new samples near N in training set can be more easy to classified correctly. Given the training data x and y , it can seeks the optimal solution.

The linear discriminant function is $g(x) = w^T x + w_0$, and then the distance between sample x and the decision boundary ($g(x) = 0$) is given by

$$\frac{|w^T x + w_0|}{\|w\|}. \quad (3.10)$$

Scaling Wand w_0 by a positive constant does not change the boundary, to make the values of Wand w_0 unique, we add the requirement to support vectors:

$$|w^T x + w_0| = 1. \quad (3.11)$$

This distance from support vectors to the largest margin hyperplane is $1/\|w\|$, margin is given by $2/\|w\|$, and the maximizing the margin is the same as minimizing $\|w\|$. we can phrase the task of finding the decision boundary in SVM as an optimization problem:

To minimize

$$J = \frac{1}{2} \|w\|^2 \quad (3.12)$$

The objective of SVM is to maximize the margin $2/\|w\|$

$$\begin{cases} w^T x_i + w_0 \geq 1 \\ w^T x_i + w_0 \leq -1. \end{cases} \quad (3.13)$$

subject to the constraints $y_i(w^T x_i + w_0) \geq 1, \forall i$

$$\text{Here } \begin{cases} y_i = +1, \forall x_i \in \omega_1 \\ y_i = -1, \forall x_i \in \omega_2. \end{cases} \quad (3.14)$$

Using Lagrange multipliers to include the constraints:

$$\mathbf{L} = \frac{1}{2} \|w\|^2 - \sum_{i=1}^N \lambda_i [y_i(w^T x_i + w_0) - 1], \quad (3.15)$$

Minimizing L relative to w and w_0 by setting the partial derivatives to zero results in:

$$w = \sum_{i=1}^N \lambda_i y_i x_i \text{ and } \sum_{i=1}^N \lambda_i y_i = 0. \quad (3.16)$$

These are the solutions for minimizing J with the constraints. The problem now is to determine the Lagrange multipliers. Once the optimal Lagrange Multipliers are obtained through some optimization procedure, we can compute w using

$$w = \sum_{i=1}^N \lambda_i y_i x_i. \quad (3.17)$$

The value w_0 can be computed using $w_0 = y_i^{-1} - w^T x_i$, where x_i is a support vector.

Using the same techniques of the linearly separable cases, we end up with a very similar optimization problem: to maximize

$$\mathbf{L} = \sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \lambda_i \lambda_j y_i y_j x_i^T x_j, \quad (3.18)$$

subject to the constraints

$$\sum_{i=1}^N \lambda_i y_i = 0 \text{ and } \lambda_i > 0, \forall i \quad (3.19)$$

L is a concave function with respect to λ

The optimization task, with x now mapped to high-dimensional space, becomes the maximization of

$$L = \sum_{i=1}^N \lambda_i - \frac{1}{2} \sum_{i=1}^N \sum_{j=1}^N \lambda_i \lambda_j y_i y_j [\Phi(x_i)^T \Phi(x_j)] = \sum_{i=1}^N \sum_{j=1}^N \lambda_i \lambda_j y_i y_j K(x_i, x_j) \quad (3.20)$$

Subject to the constraints

$$\sum_{i=1}^N \lambda_i = 0 \text{ and } 0 \leq \lambda_i \leq C, \forall i \quad (3.21)$$

We define the kernel function $K(x_i, x_j) = \Phi(x_i)^T \Phi(x_j)$

Different common types of $K(x_i, x_j)$:

1. Linear: $K(x_i, x_j) = x_i^T x_j$

2. Polynomial: $K(x_i, x_j) = (\gamma x_i^T x_j + \gamma)^d, \gamma > 0 :$
3. Radial basis function (RBF): $K(x_i, x_j) = \exp\left(-\frac{\gamma \|x_i - x_j\|^2}{2\sigma^2}\right)$

Where σ is specified by the user and common to all kernels.

3.4.2 Evaluation

It is the most common evaluative method through k-fold cross validation.

The data sample is randomly partitioned divided into k sub-samples, a separate sub-samples is retained as validation data for testing the model, other K-1 sub-samples used for training. Repeated k times to model the work, the k results from the folds then can be averaged to produce a single estimation. In this study, the model evaluation we use 10-fold cross-validation.

The overall methods as shown in Figure 3.10.



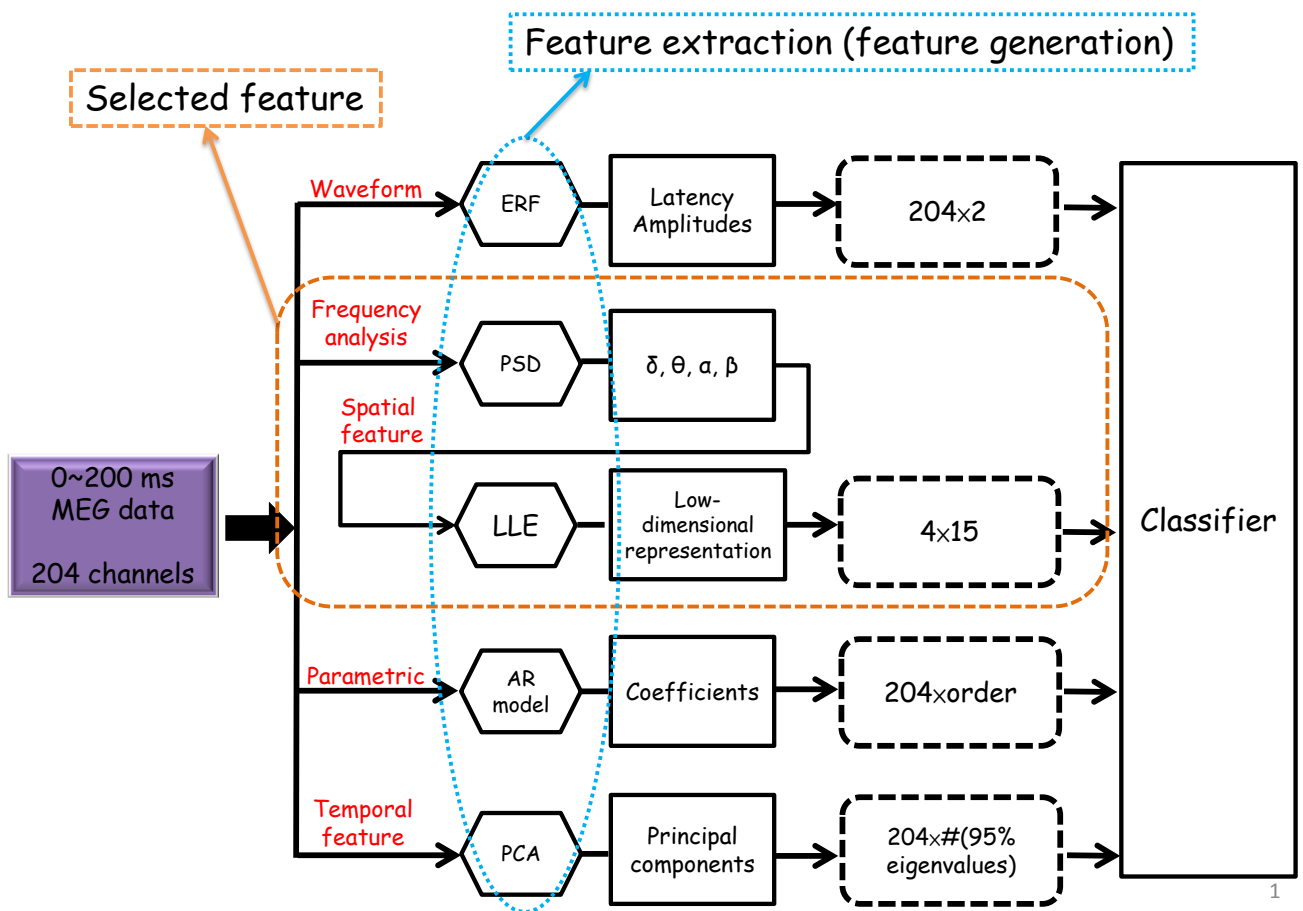


Figure 3.10: The overall methods.

Chapter 4

Experiment results



In this study, we show the recognition accuracy of the each participant in each of the feature. And then show the recognition accuracy for the discrepancy between normal subjects and BD patients.

4.1 Preprocessing results

For each condition, there are two combinations of tasks: Go-140 trials and Nogo-60 trials from total 200 trials. In Table 4.1. We preprocessed the number of trials after EOG rejection for each subject.

Table 4.1: The number of trials after EOG rejection for each subject.

NC	FgoHnogo		HgoFnogo	
	Hnogo	Fgo	Fnogo	Hgo
NC 1	55	135	45	109
NC 2	43	110	45	110
NC 3	43	107	44	107
NC 4	55	119	54	131
NC 5	55	132	51	126
NC 6	48	110	51	126
NC 7	41	92	40	93
NC 8	59	135	53	125
NC 9	55	136	53	131
NC 10	60	117	53	107
NC 11	45	115	44	120
NC 12	49	108	49	116
NC 13	54	116	58	127
NC 14	37	88	57	118

4.2 Results of all participants

We were collecting 14 participants for brain signals through the artifact removal and filter, feature extraction, and then use ten-fold cross validation method to proceed SVM classification of recognition rate, calculated each participant recognition rate and an average of all the participants recognition rate, the results shown in the Table 4.2, 4.3, and Figure 4.1 4.2.

The recognition accuracy results of each subject for PSD combine LLE feature extraction is highest recognition accuracy of 96.1% and 97.3% for FgoHnogo condition and HgoFnogo condition classification, respectively, as seen in Table 4.2, 4.3.

The recognition accuracy results of each subject for FgoHnogo condition and HgoFnogo condition classification, respectively as shown in Figure 4.1, 4.2.

Can be found from Table 4.4, 4.5, 4.3, used with the success of PSD combine LLE feature can recognition two categories of happy and fear emotion from brain signal, and get 91.8% and 91.1% of the high rate of recognition results.

4.3 Results of gender difference participants

In Table 4.6, 4.7, and Figure 4.4, the recognition accuracy of between female and male subjects for the FgoHnogo condition classification. The recognition accuracy was clearly better use the feature selection from PSD combine LLE, recognition accuracy performance of 91.2% and 91.3% for female and male, respectively.

The recognition accuracy of between female and male subjects for the HgoFnogo condition classification. Accuracy was clearly better using the feature extraction from PSD combine LLE of female and male, HgoFnogo condition accuracy performance of 92.9% and 90.7%, as shown in Table 4.8, 4.9, and Figure 4.5.

4.4 Results of BD patients

We were collecting 14 BD patients for brain signals through the artifact removal and filter, feature extraction, and then use ten-fold cross validation method to proceed SVM

Table 4.2: The recognition accuracy of each feature for each subject classification for FgoHnogo condition.

NC FgoHnogo (200ms)	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
NC 1	54.3%	55.9%	81.8%	78.5%	78.9%	90.3%
NC 2	44.4%	57.4%	84.6%	87.4%	81.7%	92.2%
NC 3	59.2%	62.5%	72.2%	70.7%	74.2%	81.4%
NC 4	60.1%	63.6%	87.0%	83.0%	83.4%	94.2%
NC 5	69.1%	72.7%	91.7%	82.9%	79.8%	96.1%
NC 6	55.5%	66.7%	86.6%	73.7%	83.6%	92.7%
NC 7	62.1%	62.5%	73.6%	64.9%	76.5%	95.8%
NC 8	60.5%	72.7%	96.6%	85.4%	88.8%	93.3%
NC 9	66.5%	60.6%	62.7%	92.8%	79.2%	84.4%
NC 10	54.2%	50.0%	90.1%	89.3%	94.2%	93.3%
NC 11	52.6%	62.5%	80.0%	65.7%	70.2%	88.4%
NC 12	60.0%	53.2%	96.6%	96.6%	96.6%	96.0%
NC 13	63.6%	60.6%	90.0%	95.7%	93.3%	95.1%
NC 14	64.8%	65.8%	87.6%	95.9%	85.4%	91.6%

Table 4.3: The recognition accuracy of each feature for each subject classification for HgoFnogo condition.

NC HgoFnogo (200ms)	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
NC 1	55.6%	66.7%	91.7%	81.8%	73.0%	88.0%
NC 2	66.7%	66.7%	77.9%	65.6%	78.1%	97.3%
NC 3	59.7%	62.5%	93.3%	89.7%	68.2%	88.7%
NC 4	63.3%	72.7%	83.3%	90.0%	92.4%	94.8%
NC 5	62.1%	60.0%	66.6%	88.9%	69.9%	91.1%
NC 6	64.9%	72.7%	87.6%	83.3%	69.9%	95.4%
NC 7	51.3%	63.9%	77.7%	83.3%	77.7%	89.2%
NC 8	60.5%	63.6%	90.0%	78.3%	74.5%	87.8%
NC 9	60.5%	58.0%	61.5%	79.2%	83.3%	89.6%
NC 10	55.7%	60.0%	83.3%	83.3%	86.7%	91.2%
NC 11	51.2%	56.3%	87.5%	69.7%	79.5%	83.8%
NC 12	60.0%	54.6%	96.6%	92.5%	90.0%	96.6%
NC 13	66.7%	51.4%	83.9%	78.1%	88.3%	92.7%
NC 14	52.6%	57.2%	87.9%	89.2%	71.9%	89.8%

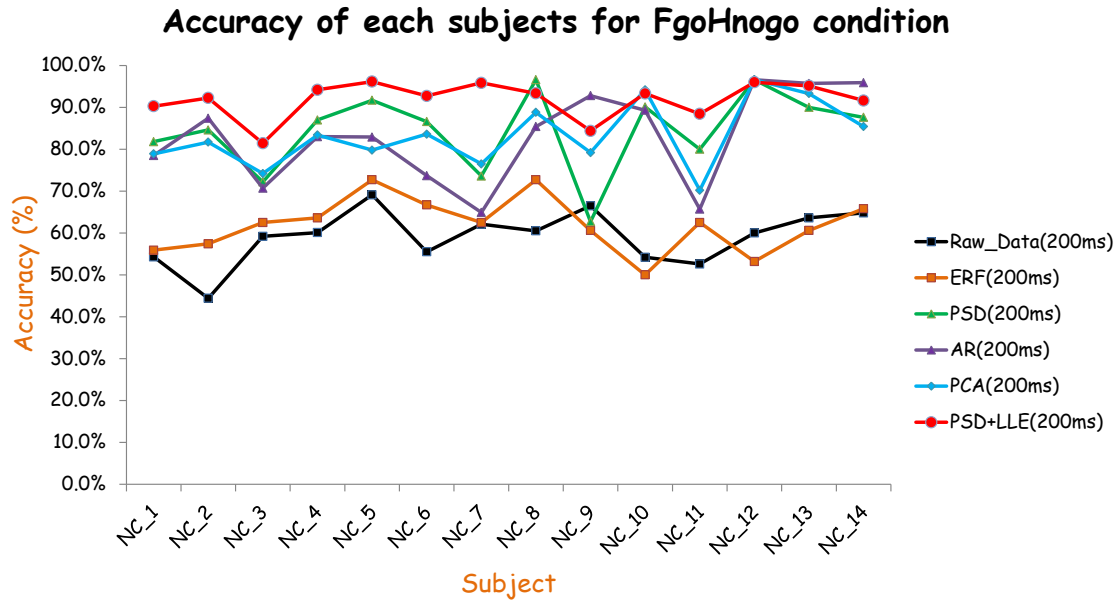


Figure 4.1: The recognition of each feature for each subject classification from FgoHnogo condition.

Table 4.4: Average each subject of each feature classification for FgoHnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	59.1%	61.9%	84.4%	83.0%	83.3%	91.8%
100ms	50.1%	54.0%	76.4%	75.1%	73.9%	86.0%

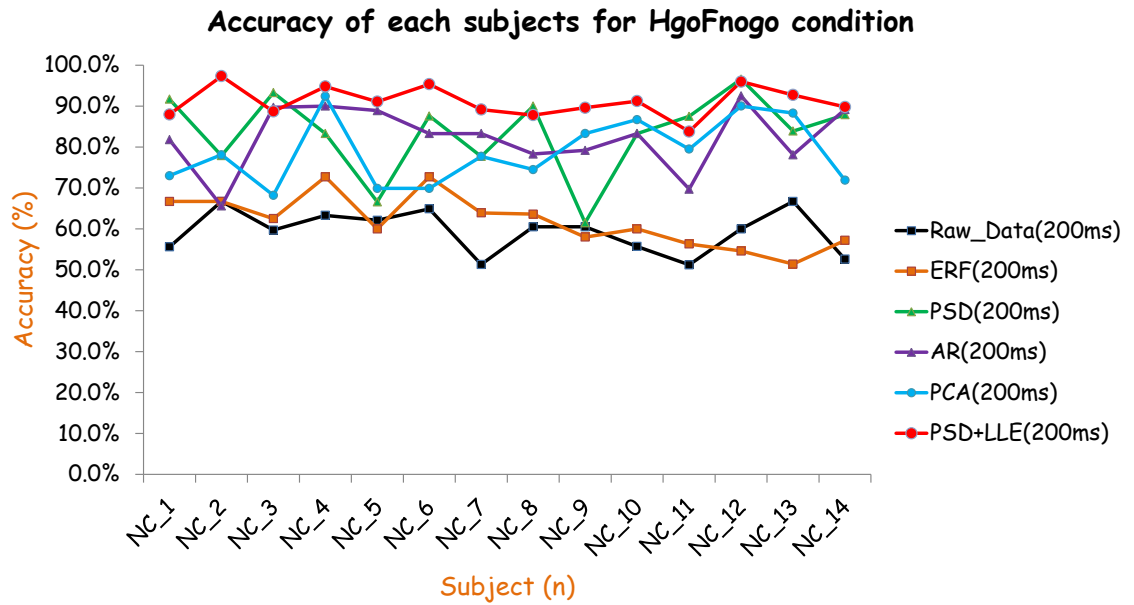


Figure 4.2: The recognition of each feature for each subject classification from HgoFnogo condition.

Table 4.5: Average each subject of each feature classification for HgoFnogo condition.

HgoFnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	59.3%	61.9%	83.5%	82.4%	78.8%	91.1%
100ms	52.9%	54.2%	81.3%	78.0%	74.2%	85.9%

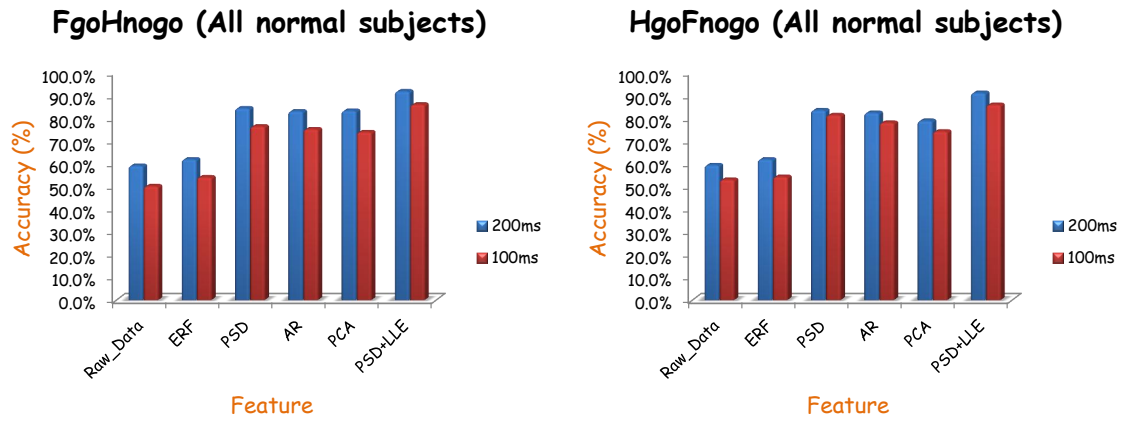


Figure 4.3: Average each subject of each feature classification.

Table 4.6: The classification results by each feature of female subjects for FgoHnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	59.1%	63.8%	81.9%	79.9%	80.7%	91.2%
100ms	50.2%	57.7%	80.0%	76.6%	75.0%	85.3%

Table 4.7: The classification results by each feature of male subjects for FgoHnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	59.0%	58.4%	88.9%	88.6%	87.9%	91.3%
100ms	49.8%	47.5%	69.8%	72.5%	71.8%	85.5%

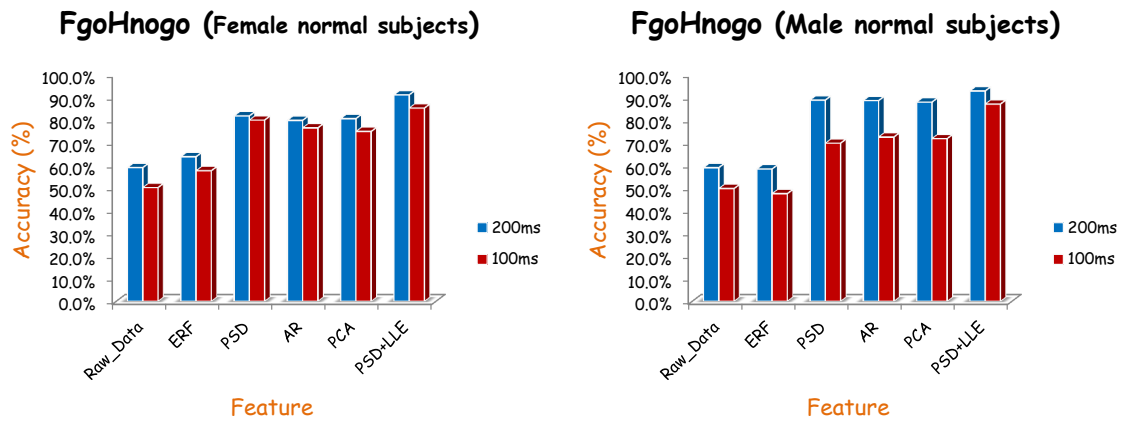


Figure 4.4: Summarized description of the classification performance obtained by each feature of both male and female subjects for FgoHnogo condition.

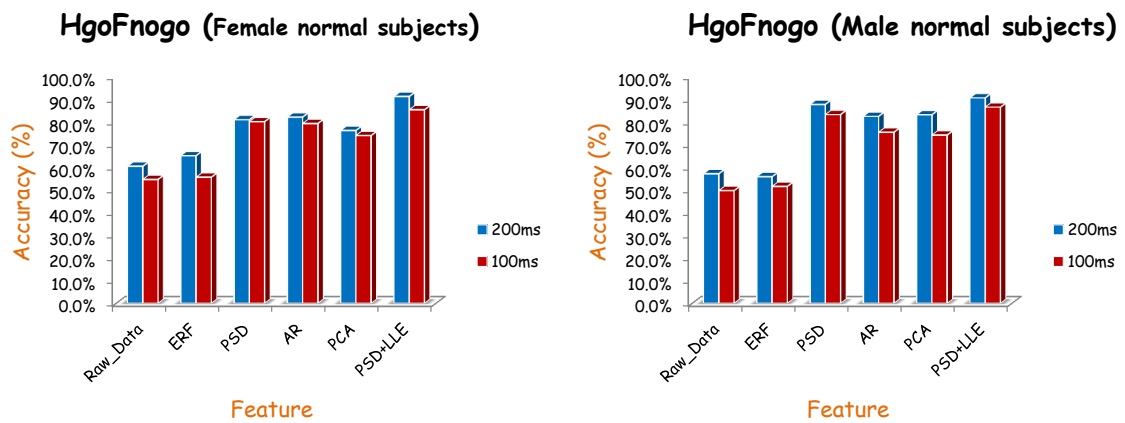


Figure 4.5: Summarized description of the classification performance obtained by each feature of both male and female subjects for HgoFnogo condition.

Table 4.8: The classification results of each feature of female subjects for HgoFnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	60.5%	65.2%	81.1%	82.2%	76.3%	92.9%
100ms	54.7%	55.7%	80.2%	79.4%	74.1%	87.1%

Table 4.9: The classification results of each feature of male subjects for HgoFnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	57.2%	55.9%	87.8%	82.6%	83.3%	90.7%
100ms	49.8%	51.6%	83.3%	75.5%	74.3%	86.6%

classification of recognition rate, calculated each participant recognition rate and an average of all the participants recognition rate, the results shown in the Table 4.10, 4.11, and Figure 4.6. The BD patients recognition accuracy is only 77.0%, the result is worse to compare NC, even though it is selected better feature.

Table 4.10: Classification accuracy for each feature averaged from the BD patients for FgoHnogo condition.

FgoHnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	30.7%	46.9%	68.9%	65.4%	62.2%	77.0%
100ms	41.1%	51.3%	58.6%	55.0%	54.4%	64.1%

Table 4.11: Classification accuracy for each feature averaged from the BD patients for HgoFnogo condition.

HgoFnogo	Raw Data	ERF	PSD	AR	PCA	PSD+LLE
200ms	44.4%	44.8%	68.9%	58.9%	59.6%	72.3%
100ms	42.3%	47.1%	58.5%	58.3%	51.2%	64.2%

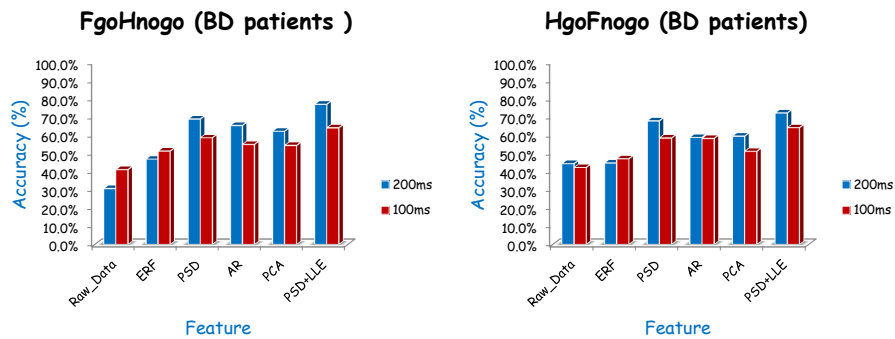


Figure 4.6: Classification accuracy for each feature averaged from the BD patients.

Chapter 5

Discussion



From this study experimental results, several research questions will be discussion as follows: (1) Classification using emotions or conditions? (2) Behavioural results, and (3) Effects of on the number of trials accuracy.

5.1 Classification using emotions or conditions?

Our experiments have eight different combinations of conditions and task: (1) FgoHnogo - Hnogo (2) FgoHnogo - Fgo (3) HgoFnogo - Fnogo (4) HgoFnogo - Hgo (5) FgoOnogo - Onogo (6) FgoOnogo - Fgo (7) HgoOnogo - Onogo (8) HgoOnogo - Hgo, as shown in Figure 5.1, however, in this study, we have only used four kinds of conditions to classify emotions, as shown in Figure 5.2. In order to determine whether to recognize the difference conditions, therefore, we have to test: use the FgoHnogo - Fgo and HgoFnogo - Hgo as training data and the FgoHnogo - Hnogo as test data, from the testing recognition results, we can see the testing data will be classified into HgoHnogo - Hgo with accuracy 4.4% (one subject), 6.0% (one subject), and 0% (other subjects).

Then we use the task to have nothing to do with emotion to verify, first using FgoOnogo - Fgo and HgoOnogo - Hgo as testing data, respectively. We found the testing data will be classified into FgoHnogo - Fgo with accuracy 63.0% (one subject), 90.7% (one subject), and 100% (other subjects) of FgoOnogo - Fgo, and HgoOnogo - Hgo will be classified into HgoFnogo - Hgo with accuracy 57.0% (one subject), 87.0% (one subject), and 100% (other subjects), as shown in Figure 5.5, 5.6. Finally, we using FgoOnogo - Onogo and HgoOnogo - Onogo as testing data, respectively, as shown in Figure 5.3, 5.4, the results found it will be accompanied by conditions in which the effects of the emotion pictures, we can get that will be affected by different conditions. Therefore, we must distinguish the different conditions of individual recognition.

5.2 Behavioural results

In this study, we use Go and Nogo task to verify the subject's emotions, because each subject's different viewpoint on the emotion, we use the Go and Nogo task of false-alarm

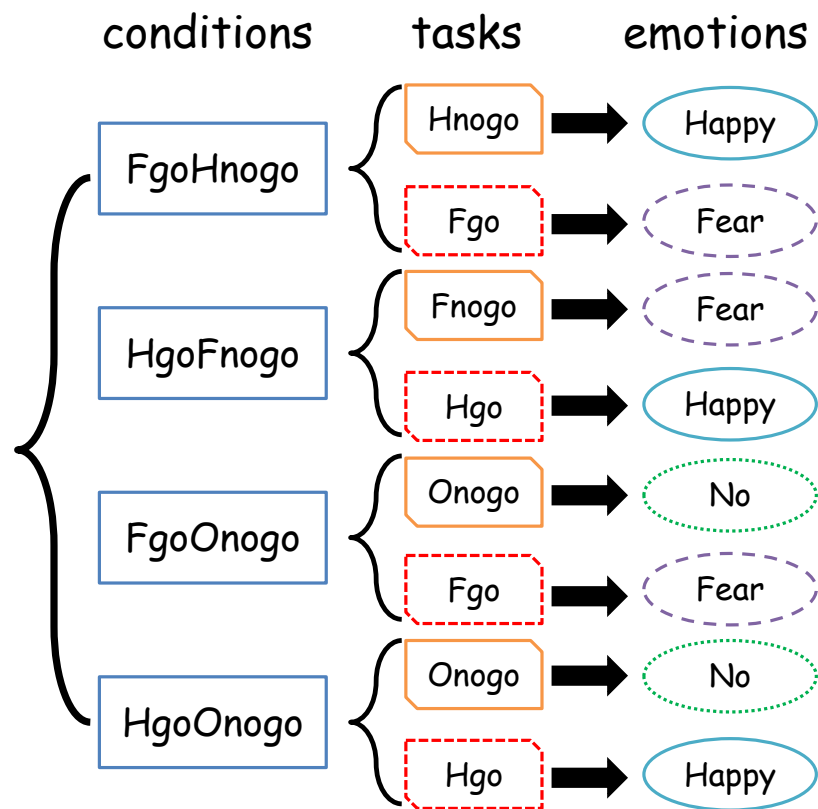


Figure 5.1: The experiments have eight different combinations.

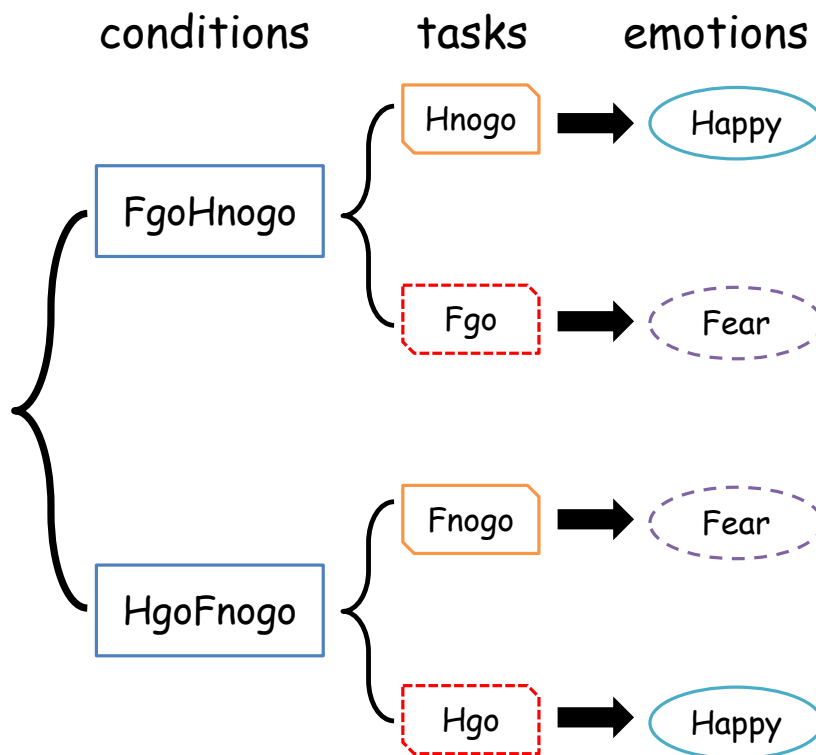


Figure 5.2: We have only used four kinds of conditions to classify emotions.

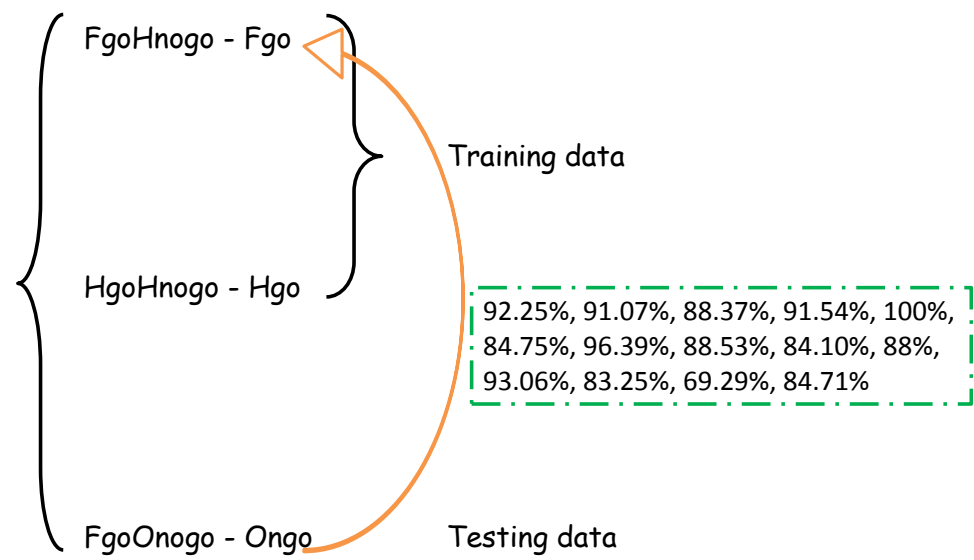


Figure 5.3: The results of use of FgoOnogo - Onogo as testing data.

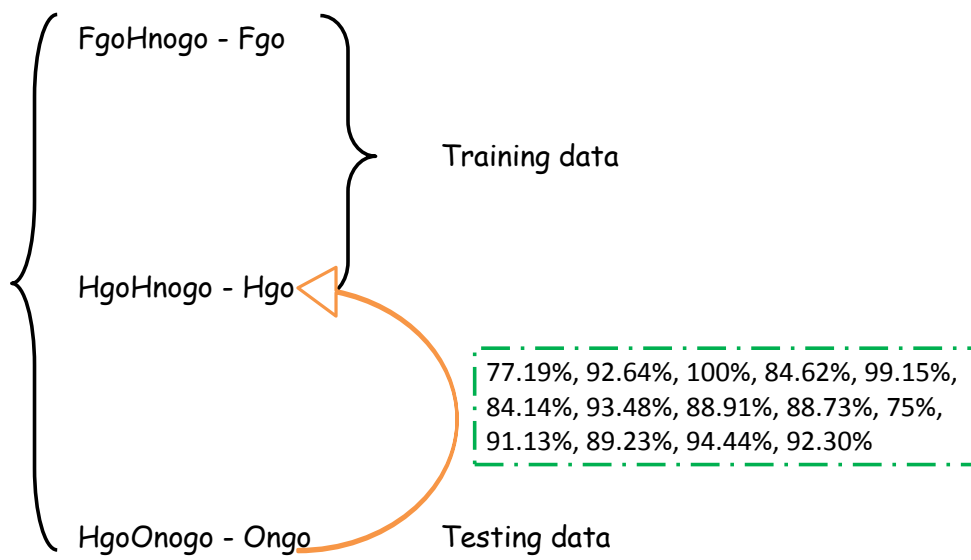


Figure 5.4: The results of use of HgoOngoo - Ongoo as testing data.

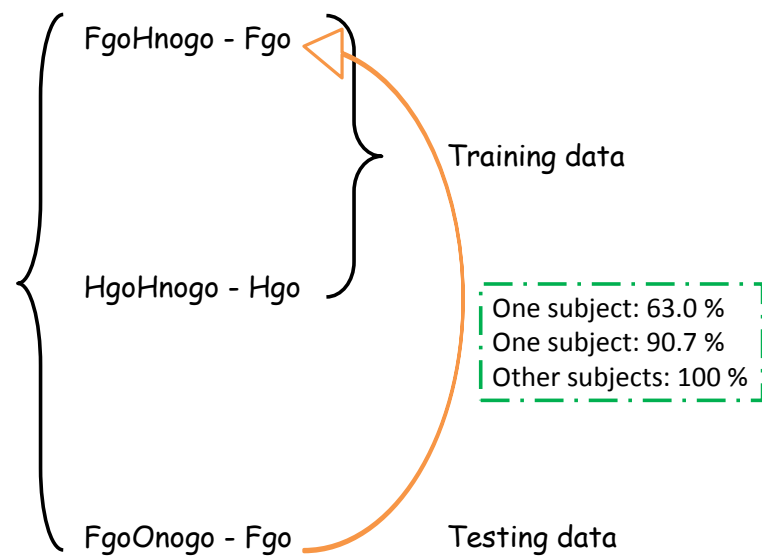


Figure 5.5: The results of use of FgoOngo - Fgo as testing data.

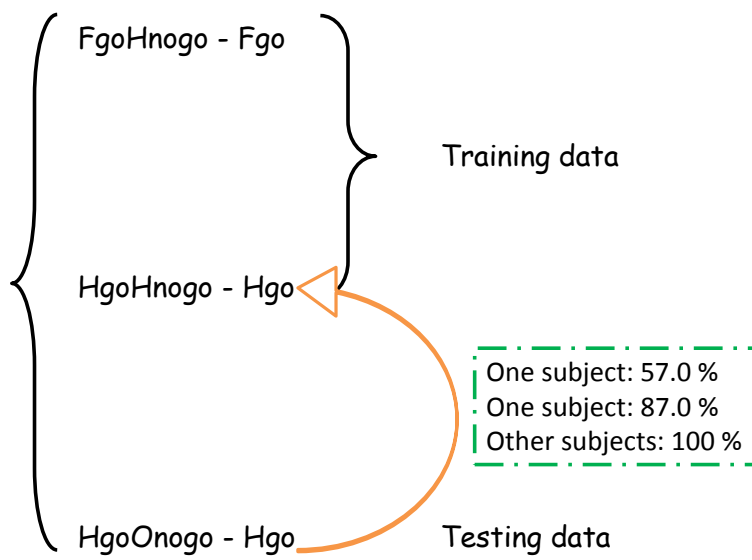


Figure 5.6: The results of use of HgoOngo - Hgo as testing data.

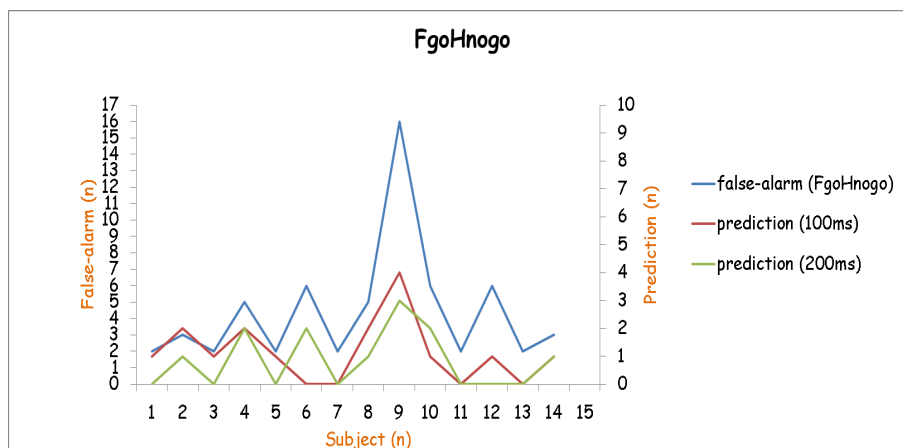


Figure 5.7: The proportion of false-alarm and prediction for FgoHnogo condition.

the results with the results of also prediction the wrong, to explore whether there is any relationship between false-alarm and also prediction the wrong result. This can be seen in Figure 5.7, 5.8, the false-alarm corresponds to also prediction the wrong result is not a trend. The analysis was conducted of the data in Table 5.1, 5.2, and from the results of that analysis, this proportion is 19% and 13%, therefore, the false-alarm and also prediction the wrong result is not relevant.

5.3 Effects of on the number of trials accuracy

In this study, there are 200 trials combinations of each condition, due to recorded MEG signals are usually contaminated with noises, the preprocessing procedure is before the feature extract, we were remove EOG interference, the removal of EOG will also remove some of useful information of signals. When the subjects were rejected a lot of EOG, this is not a good measurement situation, therefore, we want to explore, whether a correlation

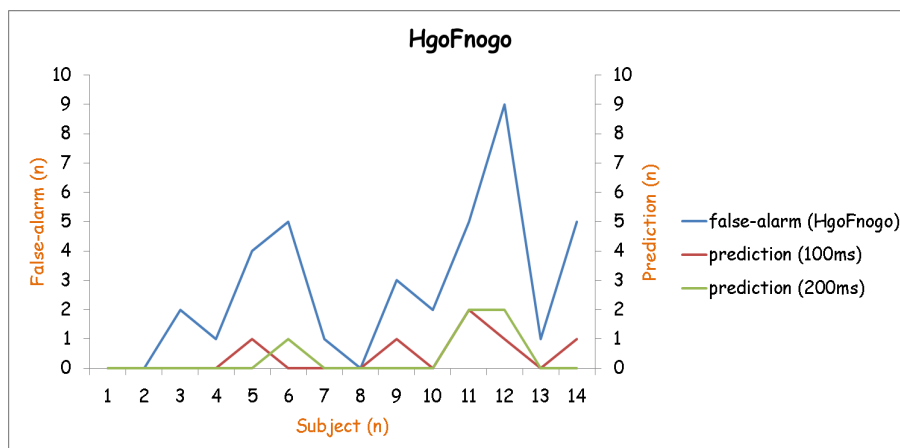


Figure 5.8: The proportion of false-alarm and prediction for HgoFnogo condition.

Table 5.1: The proportion of false-alarm and also prediction the wrong result for FgoHnogo condition.

FgoHnogo	False-alarm	Prediction
NC 1	2	0
NC 2	2	0
NC 3	2	0
NC 4	2	0
NC 5	2	0
NC 6	2	0
NC 7	3	1
NC 8	3	1
NC 9	5	2
NC 10	5	1
NC 11	6	2
NC 12	6	2
NC 13	6	0
NC 14	16	3
total	62	12
proportion	19%	

Table 5.2: The proportion of false-alarm and also prediction the wrong result for HgoFnogo condition.

HgoFnogo	False-alarm	Prediction
NC 1	0	0
NC 2	0	0
NC 3	0	0
NC 4	1	0
NC 5	1	0
NC 6	1	0
NC 7	2	0
NC 8	2	0
NC 9	3	0
NC 10	4	0
NC 11	5	1
NC 12	5	2
NC 13	5	0
NC 14	9	2
total	38	5
proportion	13%	

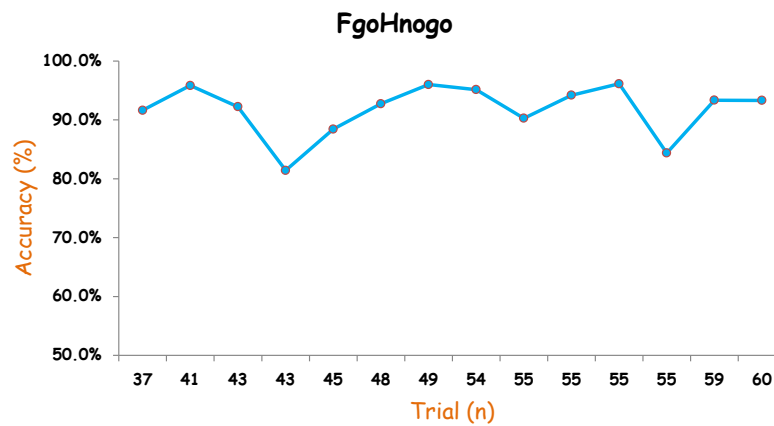


Figure 5.9: The correlation between trials and accuracy for FgoHnogo condition.

exists between the number of trials and accuracy.

This can be seen in Figure 5.9, 5.9, the number of trials corresponds to the accuracy is not a trend. A statistical analysis was conducted of the data in Table 5.3, 5.4, and from the results of that analysis, this correlation coefficient is 0.19 and 0.23, therefore, the number of trials and accuracy is not relevant.

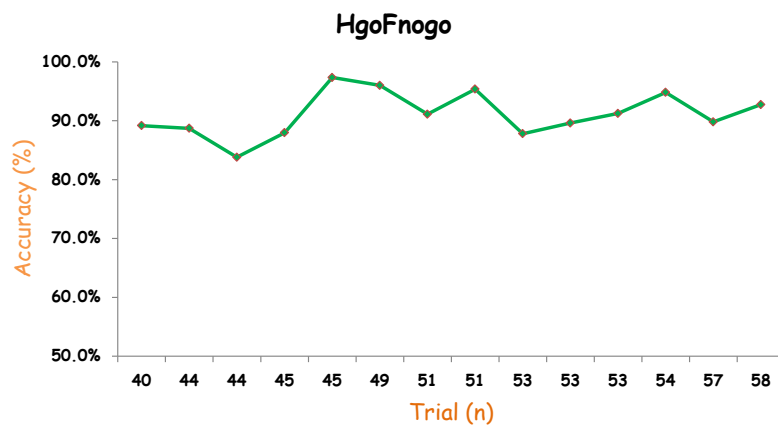


Figure 5.10: The correlation between trials and accuracy for HgoFnogo condition.

Table 5.3: The correlation between the number of trials and accuracy for FgoHnogo condition.

FgoHnogo	The number of trials	Accuracy
NC 1	55	90.3%
NC 2	43	92.2%
NC 3	43	81.4%
NC 4	55	94.2%
NC 5	55	96.1%
NC 6	48	92.7%
NC 7	41	95.8%
NC 8	59	93.3%
NC 9	55	84.4%
NC 10	60	93.3%
NC 11	45	88.4%
NC 12	49	96.0%
NC 13	54	95.1%
NC 14	37	91.6%
correlation coefficient	0.19	

Table 5.4: The correlation between the number of trials and accuracy for HgoFnogo condition.

HgoFnogo	The number of trials	Accuracy
NC 1	45	88.0%
NC 2	45	97.3%
NC 3	44	88.7%
NC 4	54	94.8%
NC 5	51	91.1%
NC 6	51	95.4%
NC 7	40	89.2%
NC 8	53	87.8%
NC 9	53	89.6%
NC 10	53	91.2%
NC 11	44	83.8%
NC 12	49	96.0%
NC 13	58	89.8%
NC 14	57	92.7%
correlation coefficient	0.23	

Chapter 6

Conclusions



In this study, we adopted the MEG signals for recognize emotion by affective visual stimuli from the healthy and BD patients.

We used five kinds of feature extraction methods were evaluated in this work, including: event-related magnetic fields (ERF), power spectral density (PSD), autoregressive (AR) model, principal component analysis (PCA), and locally linear embedding (LLE). We adopted the features and the combination of PSD and LLE as use support vector machine (SVM) to categorize happy and fear emotions. According to our experiments, the proposed system can achieve 91.8% accuracy of emotion recognition.



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