ICA BASED EEG ENERGY SPECTRUM

FOR DETECTION OF NEGATIVE EMTION BY EEG

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SUMMARY

In recent years, there are increasing interests in emotion-measurement technologies with the widespread hope that they will be invaluable in the safety, medical and criminal investigation. In the literature, various efforts have been put in the emotion measurement methods, including facial recognition, voice recognition, and electrophysiological based measurements. Among them, Electroencephalogram (EEG) might be one of the most predictive and reliable physiological indicators of emotion. However, most previously published research findings on EEG changes in relationship to emotion have found varying, even conflicting results, which could be due to methodological limitation. It needs further research before we can eventually come out with an EEG-based emotion monitor.

For detection of anxiety emotion by EEG measurement, an Independent Component Analysis (ICA) based energy spectrum feature is presented. In this study, EEG measurements on human subjects with and without anxiety emotion were conducted, the measured data was decomposed using ICA into a number of independent components, and all the independent components were loaded on an energy mapping system that shows the locations of the independent components on the scalp. By counting the number of independent components fall into both sides of the anterior temporal, clear correlation between the number of independent components on both sides of the anterior temporal and the status of anxiety emotion was observed. The results from all the subjects tested showed that in both sides of the anterior temporal, the number of independent components for anxiety status was 50% to 100% higher than that of emotion void status. The ability of this ICA-based method was verified by SVM prediction accuracy. Prediction accuracy shows that there is a high probability to develop subject-specific negative emotion monitoring system.

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1. INTRODUCTION

1.1. Background

Emotion is a common phenomenon in our daily life. One common definition of emotion in medicine is that emotion is the “mental state, periodic or dispositional, associated with certain physiological conditions, and brought about by thoughts and happenings perceived as desirable or undesirable.” (O’Shaughnessy 1992) An example of a periodic emotional state is the academic’s joy at solving a tricky intellectual conundrum; an example of an emotional dispositional state is the sympathy that disposes people to help others. All emotional states are characterized by bodily effects on pulse rate, blood pressure, adrenal secretion, blushing, trembling, crying, fainting, and so on.

Many psychologists adopt the ABC model, which defines emotions in terms of three fundamental attributes: A. physiological arousal, B. behavioral expression (e.g. facial expressions), and C. conscious experience, the subjective feeling of an emotion. (Myers 2004) All three attributes are necessary for a full fledged emotional event, though the intensity of each may vary greatly. There are three major theories to expound the relationship among these three components, which are James-Lange Theory (James 1890), Cannon-Bard Theory (Cannon 1927) and Schacter’s Two-factor Theory (Schachter 1971).

James-Lange Theory, which was proposed by William James & Carl Lange, is one of the earliest theories about emotion. In this theory, the experience of emotion is awareness of physiological responses to emotion-arousing stimuli. The emotion-triggering stimulus notifies the sympathetic branch of the autonomic nervous system (cause body's arousal), and then the signal will transfer from the sympathetic branch to the brain's cortex, lead to subjective awareness. (Figure 1.1)

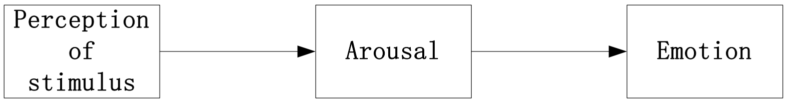


Figure 1.1 James-Lange Theory

However, evidence for James-Lange's theory seemed improbable because the evidence suggested that our physiological responses are not distinct enough to evoke different emotions. For example, does the racing heart signal mean the fear, anger, love or excited? Also, many physiological changes happen slowly, too slowly to trigger sudden emotional changes. So Walter Cannon & Philip Bard proposed Cannon-Bard Theory, which is that physiological arousal and our emotional experience occur simultaneously. The emotion-triggering stimulus notifies both the brain's cortex (subjective awareness) and the sympathetic branch of the autonomic nervous system (causes body's arousal). (Figure 1.2)

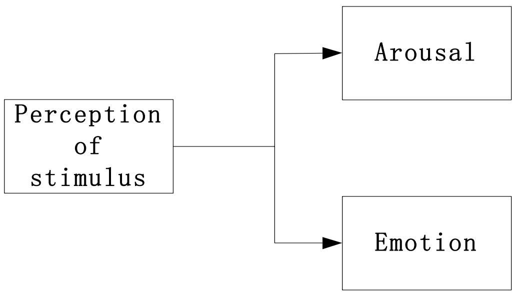


Figure 1.2 Cannon-Bard Theory

However, Cannon-Bard Theory didn't explain the relationship between the emotion and thoughts. Most psychologists today believe that our cognitions, such as our perceptions, memories, and interpretations, are essential ingredient of emotions. Stanley Schachter proposed his famous two-factor theory in which emotions have two ingredients: interaction between physical arousal and cognition ("label"), which means to experience emotion one must be both physically aroused and cognitively label the arousal. And the physical arousal can intensify most emotions. (Figure 1.3)

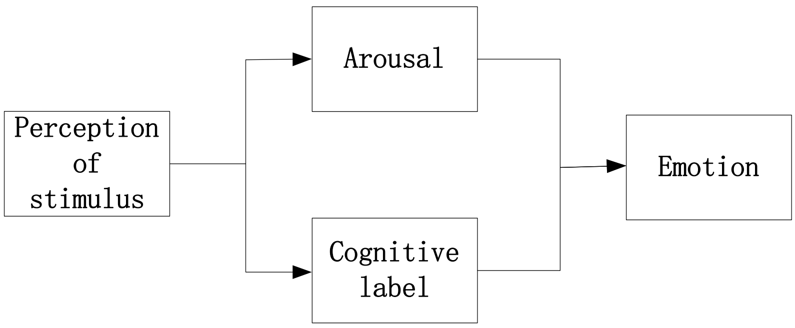


Figure 1.3 Schachter's two-factor Theory

1.2. Problem Statements

Emotional intelligence consists of the ability to recognize, express, and have emotions, coupled with the ability to regulate these emotions, harness them for constructive purposes, and skillfully handle the emotions of others. The skills of emotional intelligence have been argued to be a better predictor than IQ for measuring aspects of success in life (D.Goleman 1995). Scientists have amassed evidence that emotional skills are a basic component of intelligence, especially for learning preferences and adapting to what is important (Mayer 1990; Salovey 1990;

J.LeDoux 1996).

With increasing deployment of adaptive computer systems, the ability to sense and respond appropriately to user emotion feedback is of growing importance. A failure to include the emotional component in human-computer interaction is comparable to trimming the potential bandwidth of the communication channel. Frustrating interaction with a computer system can often leave a user feeling negatively disposed to the system and its makers. Since humans are predisposed to respond socially to computers, such negative experiences could alter perceptions of trust, cooperation and good faith on the part of the user. On the other hand, enabling computers to recognize and adapt to the user's emotion state can, in theory, improve the quality of interaction (Preece 1994; Klein 2002; Bickmore 2004; Mishra 2004).

Due to the infinite extension of emotional phenomena, it is impossible to make a full description of all the emotions that we can experience. So emotion is divided into two groups: positive emotions (such as: I feel well, happy, healthy, strong, and so on) & negative emotions (such as: I feel uncomfortable, unfortunate, sick, sad, lonely, anxiety, and so on).

It is fair to say that not all computers need to be aware of the user's emotions because most machines are only rigid tools. However, there is a range of areas in HCI where computers need to adapt to their users' emotions (Bloom 1984). Literatures on emotion theory points out:

Firstly, positive emotion is much harder to elicit in the laboratory in compared with negative emotion. This phenomenon refers to the general tendency of organisms to react more strongly to negative compared with positive stimuli, perhaps as a consequence of evolutionary pressures to avoid harm.

Secondly, with increased levels of adrenaline and other neuron-chemicals coursing through the body, a person engulfed by negative emotions has diminished abilities with respect to attention, memory retention, learning, creative thinking and polite social interaction. For example: Stress, anxiety and frustration experienced by a learner in the educational context can degrade learning outcomes (Kahneman 1973; Isen 1987; Lewis 1989).

Furthermore, for the safety, security and many other reasons of some careers, such as the pilots, it is important to monitor or detect the operators' emotion states. If the pilots are in the state of negative emotions for a long period of time, it is more likely for him or her to make the mistakes, which will cause tremendous loss. Thus, it is important and useful to detect negative emotions.

1.3. Research Objectives

The main objective of this research is to propose and develop a new physical quantity, which is named ICA-based EEG Energy Spectrum, for the features in identifying subtle changes in the EEG signal in relationship to negative emotions. Under this primary objective, the detailed sub-objectives are the following:

1) To establish the analysis of this physical quantity;
2) To establish the experiments for verifying the effectiveness of this physical quantity, which includes the protocol design, experimental design and the critical electrodes placement design for the negative emotion detection by using EEG;
3) To analyze the experiment results for the effectiveness of this physical quantity;
4) To verify the results for this physical quantity by using Support Vector Machine (SVM).

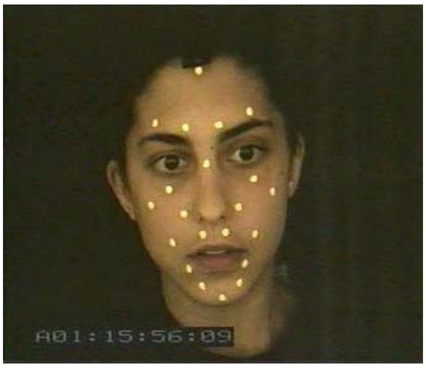
2. LITERATURE REVIEW

2.1 Traditional Technologies in emotion detection

Traditional technologies in emotion detection and prediction mainly focus on the facial expression recognition, verbal signal and other physiological signals detection, such as heart rate, respiration rate, and so on. The different emotion detection technologies will be summarized and the specific technologies will be discussed.

2.1.1 Facial Analysis technologies

People's facial expressions are thought to be very reliable signs of their emotional reaction to various stimuli. The principle of this method is that different emotion has different combination of the contractions of facial muscles. So a camera is used to monitor several dots in the user's face (Figure 2.1a), and each dot position represent one special muscle contraction state (Figure 2.1b). (Ekman 1972) When the user expresses different emotion, the relation dot position will be changed, and according to these relation position changes, the computer will analyze and determine what emotion state the user is now in. The well known Facial Action Coding System (FACS) was developed by Paul Ekman and W.V. Friesen in the 1970s (Ekman 1972).



(a) Facial action coding point (b) Facial muscles

Figure 2.1 Facial emotion analyses

However, several important problems(Enns 1991; He 1992; Wang 1994; Suzuki 1995; Smilek 2000), such as the face is not in the focus of the attention, the face orientation changing, face surface changing and the global representation of a face, can affect the emotion detection results by this method.

2.1.2 Speech Recognition technologies

A lot of researchers work on extracting emotional content from human voice as another technique for affective input. Speech recognition is a difficult problem in itself. There are problems with surrounding and disturbing sounds, problems with dialects and personality in the human voice. And if all that is solved there are also problems with understanding the actual meaning of what is being said. The same word can mean so many different things depending on its context and how it is being said. Researchers have come so far that they can work with a defined set of words in a relatively quiet environment. The emotional value of what is said and how it is said is yet another problem to researchers. There are not yet any fully developed prototypes using this method for affective input. Before that happens, researchers will have to work on the problem of defining the characteristics of emotional states expressed in speech. Cowie and colleagues point out the importance of working with naturally expressed emotions and not acted data which is the most common approach (Fotinea 2003). They have noted several characteristics not previously defined such as impaired communication and articulation. Acted data is most often based on monologue whereas spoken emotional reactions are more common when interacting with another part. Breakdowns and disarticulation are two examples that may not occur in acted data. Also the patterns in pitch, volume and timing are also other problems in the emotion detection via speech recognition.

2.1.3 Tradition methods disadvantages

There are some other methodologies based on other physiological signals to detect emotion, such as heart beat, respiration rate, and so on. All these methods are immature and have many problems such as low accuracy and low efficiency, and so on. From biological basis, these physiological are all controlled by the human brain. So EEG, which is noninvasive to directly monitor the brain signal, becomes one of prominent alternatives to detect emotions.

2.2 EEG-Based Emotion Measurement

A large number of researches have been conducted on the emotion measurement.

Since Dr. Hans Berger, a German neuron-psychiatrist, published his first EEG recording in 1929 (Berger 1929), EEG has been acclaimed as one of the most promising tools, sensed via an array of small electrodes affixed to the scalp, and examining alpha, beta and theta brain waves to investigate the brain function. Particularly, with the development of computer technology, EEG plays a significant role nowadays in the EEG-based clinical diagnosis and studies of brain function (Van 1950; Jongh 2001; Lehnertz 2001; Benar 2003; Thakor 2004). In addition, there are various research findings showing that different mental activities, either normal or pathological, produce different patterns of EEG signals (Miles 1996). EEG was used to detect emotion since 1970s. And from the experiment design aspect, there are mainly two type approaches to use EEG to detect emotion: Event-Related Potentials (ERPs) and Cerebral Electricity Asymmetry.

2.2.1 Event-Related Potentials (ERPs)

The hypothesis of this method is that event-related potentials vary with the judged emotionality of picture stimuli. Specifically, a widely distributed, late positive potential (LPP) is enhanced for stimuli evaluated as distant from an established affective context.

To test this hypothesis, Cacioppo and colleagues (Cacioppo 1993; Cacioppo 1994; Cacioppo 1994; Cacioppo 1996) measured ERPs in response to positive and negative pictures that were rated as equally extreme in valence and arousal. They put rare emotional pictures (positive or negative) into a series of frequent neutral pictures and showed the pictures one picture per second to the participants. At the same time, the EEG signal was recorded from F3, Fz, F4, C3, C4, P3, Pz, P4, A1, and A2 of international 10-20 EEG standard electrode positions (Figure 2.2). After that, participants were instructed to evaluate the pictures and to report their evaluations after the picture disappeared. The result was that a pleasant target stimulus presented within a series of unpleasant pictures elicits a larger LPP than does the same pleasant target, presented among other pleasant stimuli. (Figure 2.3)

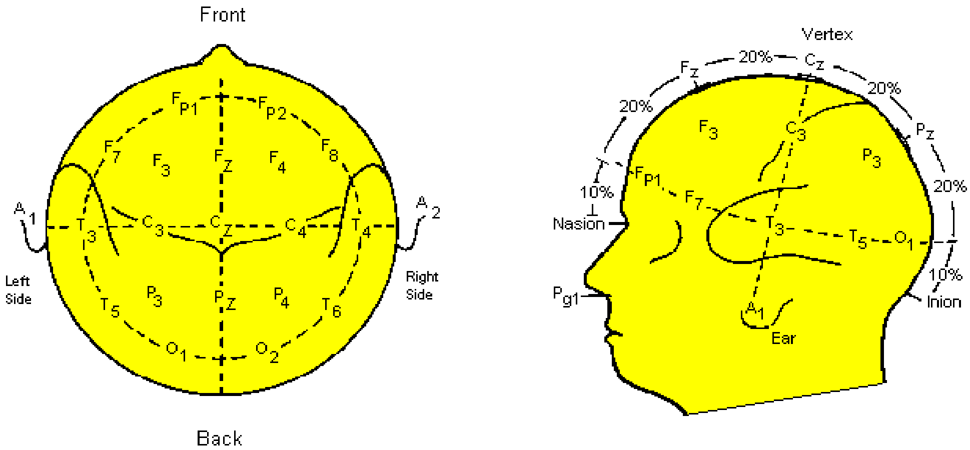


Figure 2.2 International 10-20 EEG standard electrode positions

Similar results are found for unpleasant targets (in a pleasant series) for this affective oddball paradigm. Furthermore, the greater the affective distance of a target (the greater its valence difference from the series) the larger the late potential. These findings appear to parallel results obtained with conventional, non-affective oddball tasks, in which a rare stimulus event (e.g. a high tone preceded by a series of low tones) elicits larger late positivity (P300) than a stimulus consistent with the context (Donchin 1988). The LPP in the affective oddball paradigm differs somewhat from the traditional, non-affective P300 in that it usually occurs later, and appears to be partially lateralized-with larger LPP amplitudes over the right than the left parietal hemisphere (Cacioppo 1994).

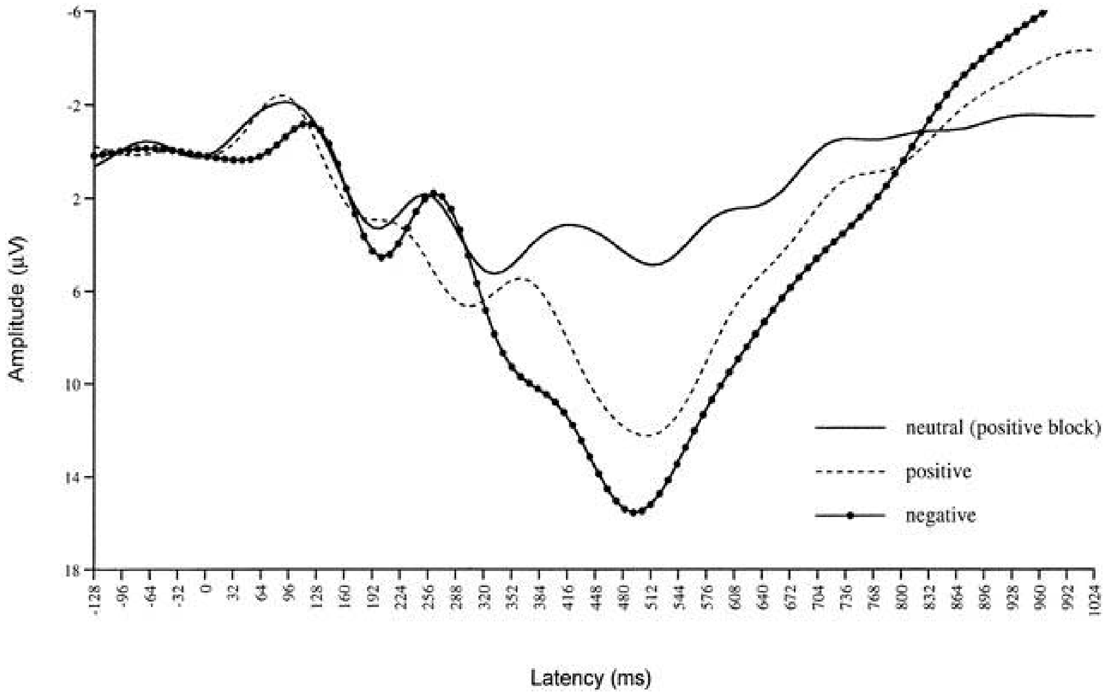


Figure 2.3 Using ERPs to differentiate negative/positive emotions

However, positive and negative pictures do not produce qualitatively different responses, such as there is no different direction of ERPs, and there are no different ERPs in different locations, and so on. Hence, ERPs can at best represent the arousal dimension of emotion, but not the valence dimension. Moreover, a similar positive activation is found for any rare stimuli in a series of frequent stimuli (e.g., a high tone in a series of low tones). Hence, the ERPs may reflect surprise, but not emotional responses to the content of the pictures. Thus, it is not suitable to use ERPs to detect or measure the negative emotions.

2.2.2 *Cerebral Electricity Asymmetry*

The other main approach is based on the cerebral electricity asymmetry for emotional processes. Since 1970s, scientists have found that there is cerebral lateralization for emotional processes which have two main formulations. The results of some studies (Carmon 1973; Gardner 1975; Davidson 1976; A 1977) seemed to suggest that the right hemisphere was more involved than the left in subserving emotional processes. Other studies (Gainotti 1972; Dimond 1977; Ahern 1979; L 1985), however, have suggested the existence of a differential lateralization for positive and negative emotion, in which the left hemisphere is more involved in the mediation of positive emotion and the right hemisphere is more involved in the mediation of negative emotion.

More and more researchers (Masaoka 2000; Davidson 2001; Hariri 2003; Davidson 2004; Hare 2005) supported the second hypothesis. Using a variety of methods to make inferences about regionally specific patterns of activation, many investigators have now reported systematic asymmetries in patterns of activation in specific brain regions in response to certain types of positive and negative emotional challenges.

For example, Schmidt et al (Schmidt 2002) measured EEG asymmetries while participants were listening to positive (happy) and negative (fear/sad) musical excerpts. The EEG signal was collected from F3, F4, Cz, P3 and P4 and two more electrodes were used to detect EOG. All the collected EEG data were visually scored for artifact due to eye blinks, eye movements, and other motor movements and all artifact-free EEG data were analyzed using a discrete Fourier transform (DFT), with a Hanning window of 1s width and 50% overlap. Power (micro-volts-squared) was derived from the DFT output in the alpha band (8-13 Hz); a natural log (ln) transformation was performed on the EEG data to reduce skewness. As expected, happy music increased left-right asymmetries, whereas sad and fearful music decreased left-right activity. (Figure 2.4)

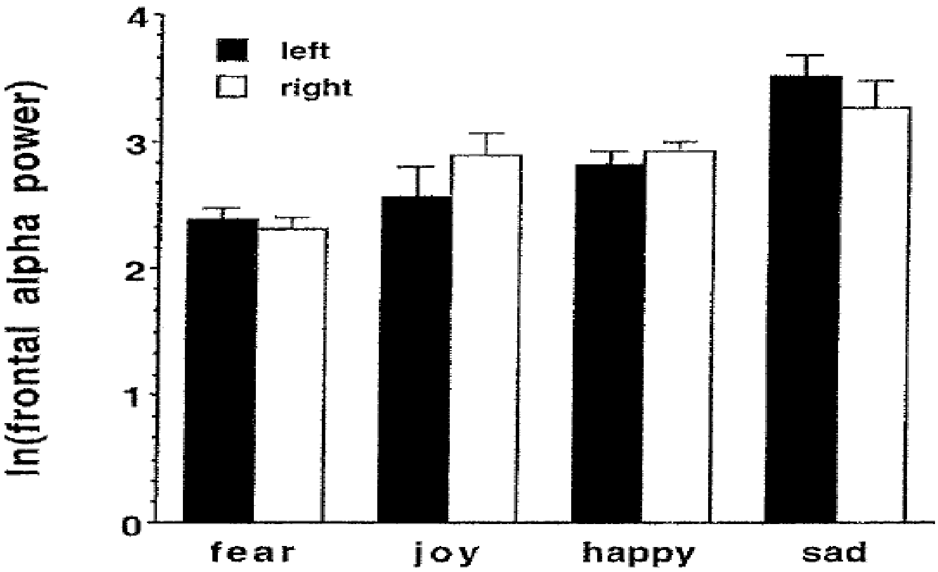


Figure 2.4 Emotion detection using brain asymmetry

As we know that alpha power is inversely related to activity, thus lower power reflects more activity. So for negative emotions (fear and sad), the left hemisphere frontal alpha power is larger than the right hemisphere frontal alpha power, which means left hemisphere frontal activity is less than the right hemisphere frontal activity in negative emotions. So in positive emotions (joy and happy) the left hemisphere frontal activity is larger than the right hemisphere frontal activity.

Despite the complexities associated with aggregating studies with vastly different experimental designs, a recent meta-analytic review has also supported the notion that certain forms of positive and negative emotion exhibit different patterns of functional brain asymmetry, particularly in prefrontal cortical territories.

Based on a large body of both human and animal experiment studies, Davidson and his colleagues (Davidson 2003) have proposed that greater left-sided dorsolateral activity may be associated with approach-related, goal-directed action planning, whereas on a lesser level of consensus, from the neuron-imaging studies of spatial working memory, they suggested that activation of right lateral prefrontal cortex during withdrawal-related emotion may be associated with threat-related vigilance. Davidson also reported that positive and negative emotion states shift the asymmetry in prefrontal brain electrical activity in lawful ways. For example, film-induced negative emotion i.e. fear/anxiety increases relative right-sided prefrontal cortex activation, whereas induced positive emotion elicits an opposite pattern of asymmetric activation (Davidson 2003).

Furthermore, Heller and colleagues have proposed that asymmetries in parietal cortex may be associated with arousal such that greater right-sided posterior activation is associated with higher arousal emotion. And subjects exhibit stable differences in asymmetric patterns of activation in prefrontal brain regions that predict various features of affective reactivity. However, there are several issues regarding the “asymmetry” works.

Firstly, all previous emotion detection by using EEG is based on electrical asymmetry by measuring alpha band power. However, as we know, there are several factors which can affect the alpha band power, such as attention shifting, fatigue level changing, and so on. Furthermore, Mueller (1999) has reported that right frontal sites exhibited a significant increase in power for positive and negative valence relative to neutral stimuli for γ-40 power compared to the neutral condition, and also no statistically significant effect was found for alpha activity in anxiety state, indicating no sensitivity of alpha de-synchronization. All these arguments weaken the possibility of negative emotion detection by electrical asymmetry.

Secondly, all the researchers collected the EEG signal from the prefrontal and parietal surface (such as Fz, Pz, and Cz). For the prefrontal, the main function of prefrontal cortex (PFC) is the executive function, which means PFC has more complex signal that mix the signals related to emotion with other signals non-related to emotion. For the parietal, the primary sensory cortex and primary motor cortex lies there, which means parietal also has more complex signal. So it is not practical to get the emotion EEG data from prefrontal cortex or parietal part.

The third disadvantage is the signal processing methodology. Human eyes were used to recognize and grade those obvious noises, such as eye blinking, muscle movement. However, the traditional signal processing method can not work for the artifacts which have the same amplitude with the emotion-related EEG data. Also, frequency domain analysis was the main method used to analyze the results; however, there are no consistent results from different researcher, which may because of this ineffectiveness of this signal processing method.

Thus, considered the complexity of EEG signals, Independent Component Analysis (ICA) has been investigated as well as the biological basis of emotion and brain structure, a novel ICA-based EEG Energy Spectrum was proposed and used to evaluate some negative emotions, such as anxiety.

3. ICA-based EEG Energy Spectrum

This chapter describes the biological basis of ICA-based EEG Energy Spectrum, as well as the principle of ICA-based EEG Energy Spectrum, which includes Independent Component Analysis, Scalp EEG mapping, and ICA-based EEG Energy Spectrum calculation.

3.1 Biological Basis

As we know, different kinds of brain activities are the result of some neuron groups firing in the certain time sequence and certain intensity. The neuron groups' firing implies the neurons activation, which will cause peak electrical potentials to appear at specific locations on the scalp. Figure 3.1 shows some brain activities with different neurons firing pattern.

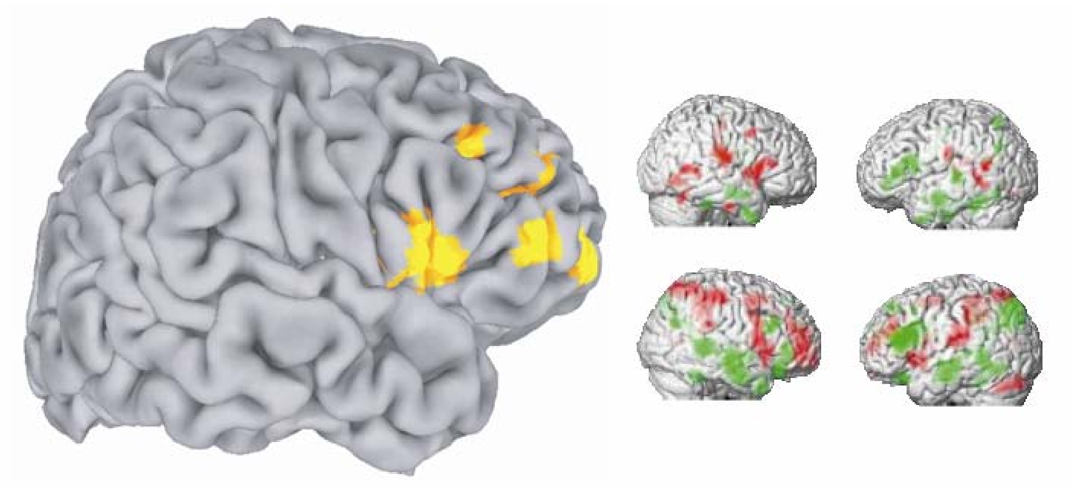


Figure 3.1 Some Brain Activities

For simplification, each of this activated neuron group can be viewed as one electrical source and all the electrical sources are independent on each other. Thus, by summarizing the peak electrical potentials appearing in the specific locations on the scalp in the certain time slot, the intensity of neuron groups' activation related to some brain activity can be determined. Here the intensity of neuron groups' firing represents the neurons activation energy.

Therefore, the specific brain activity can be monitored or measured by the number of the "peak" electrical potentials appearing in the specific locations on the scalp, and this forms the basis of ICA-based EEG Energy Spectrum. Under this principle, the calculation of ICA-based EEG Energy Spectrum consists of four steps: Independent Component Analysis, Scalp EEG Mapping, Brain Activity Classification and Statistical Analysis.

3.2 Independent Component Analysis (ICA)

Independent component analysis (ICA) is a computational method for separating a multivariate signal into additive subcomponents supposing the mutual statistical independence of the non-Gaussian source signals. This method is mainly for the blind source separation (Herault 1991; Common 1994), in which case the original independent sources are assumed to be unknown, and yet to be separated from their weighted mixtures. Furthermore, modeling of noise or artifacts is not required in ICA. Figure 3.2 is the illustration of Independent Component Analysis.

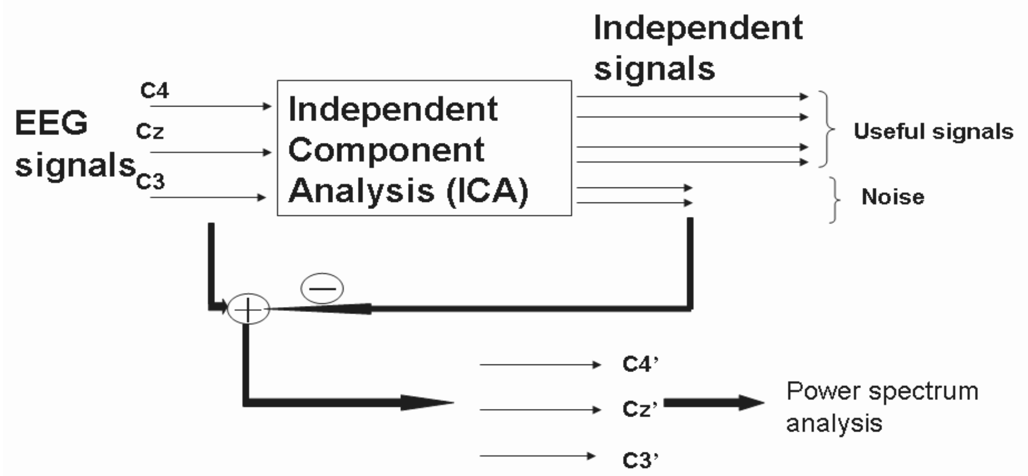


Figure 3.2 Illustration of Independent Component Analysis

3.2.1 ICA Algorithm

The basic data model used in defining (linear) ICA assumes that the observed n-dimensional data vector at time instant t, x(t) = [x1(t),…, xn(t)]T is given by

$$\mathbf{X}(t) = \sum_{i=1}^{m} \mathbf{a}_i \mathbf{s}_i(t) = \mathbf{A}\mathbf{s}(t) \qquad (3.1)$$

where $\mathbf{s}(t) = [s_1(t), \ldots, s_m(t)]^T$ are m independent source signals with zero mean, which can be guaranteed by explicitly extracting the mean of each $x_i(t)$ without loss of generality, and $\mathbf{A} = [\mathbf{a}_1, \ldots, \mathbf{a}_m]$ is a constant mixing matrix which is a function of the location of the sources, the positioning in an EEG recording, the shape and the conductivity distribution of the brain as a volume conductor (Vigario 1997). As in the general blind signal separation problem, **A** is assumed to be an n×m matrix of full rank (there are at least as many mixtures as the number of independent sources, i.e. n

> m). In addition, although **A** is unknown, we assume it to be constant, or semi-constant (preserving local constancy) in order to perform ICA.

If W denotes the inverse or pseudo-inverse of A, the problem can be redefined equivalently as to find the separating matrix W that satisfies

$$\mathbf{s}(t) = \mathbf{W}\mathbf{x}(t) \tag{3.2}$$

It has been documented that the preprocessing the input data (mixtures) by whitening can significantly ease the separation of the source signals (Karhunen 1997). Therefore, in the first step, we implement standard principal component analysis (PCA) for whitening **x**. It can be shown in the compact form (noting that we have now dropped the time index t):

$$\mathbf{v} = \mathbf{V}\mathbf{x} \tag{3.3}$$

where $E\{\mathbf{v}\mathbf{v}^{\mathrm{T}}\} = \boldsymbol{I}$ with $\boldsymbol{I}$ denotes the unit matrix. The whitening matrix **V** is given by

$$\mathbf{V} = \mathbf{D}^{-1/2}\mathbf{E}^{T} \tag{3.4}$$

where $\mathbf{D} = \mathrm{diag}[\lambda_1, \ldots, \lambda_m]$ is a diagonal matrix with the eigenvalues of covariance matrix $E\{\mathbf{x}_i\mathbf{x}_i^{\mathrm{T}}\}$ as its diagonal elements, and **E** is a matrix with the corresponding eigenvectors as its columns.

The key to estimating the independent components from their mixtures by using ICA is non-Gaussianity. Intuitively speaking, maximizing the norm of this kurtosis leads to the separation of one non-Gaussian source from the observed mixtures. In our algorithm, non-Gaussianity is measured by the classical fourth-order cumulant or kurtosis. Consider $\mathbf{y} = \mathbf{w}^{\mathrm{T}}\mathbf{v}$, with $||\mathbf{w}|| = 1$, kurtosis is calculated by

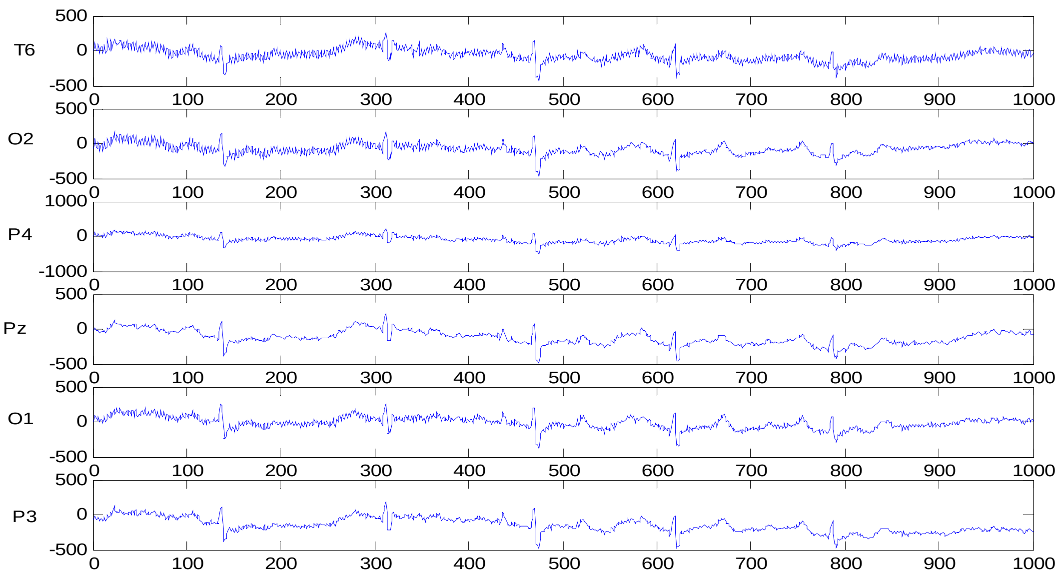
$$kurt(\mathbf{y}) = E\{(\mathbf{y})^4\} - 3[E\{(\mathbf{y})^2\}]^2 \tag{3.5}$$

where operator E denotes the mathematical expectation.

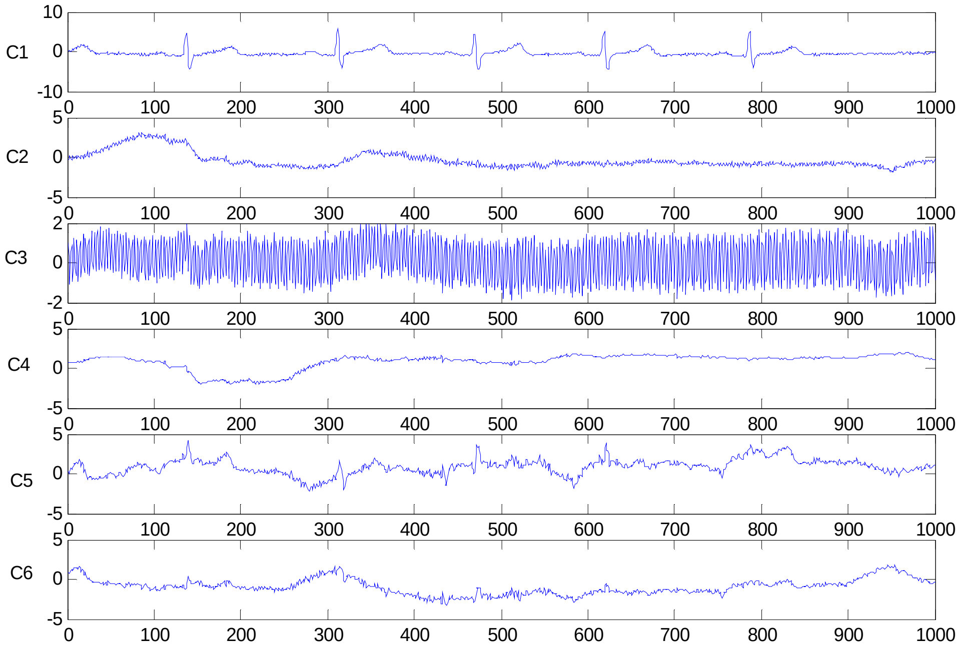
Then the FastICA fixed-point algorithm based on gradient descent searching (Hyvarinen 1999; Hyvarinen 2000) is used to search the expectation maximization. As a result, rows of the separating matrix **W** and corresponding independent sources are identified one by one, up to a maximum of m. The basic steps of this efficient algorithm are as follows:

1) Choose initial vector w_0 randomly (iteration step l=0).
2) Let $\mathbf{w}_l = E\{\mathbf{v}(\mathbf{w}_{l-1}{}^T\mathbf{v})^3\} - 3\mathbf{w}_{l-1}$.
3) Let $\mathbf{w}_l = \mathbf{w}_l / \|\mathbf{w}_l\|$.

If the stop criterion has not been satisfied, the program will go back to step 2. Due to the cubic convergence of the algorithm, the solution is typically found in less than 15 iterations. Figure 3.3 shows an example of independent component analysis.



(a) twelve seconds of anxiety emotion state EEG raw data



(b) ICs of the 12 seconds of anxiety emotion state EEG raw data

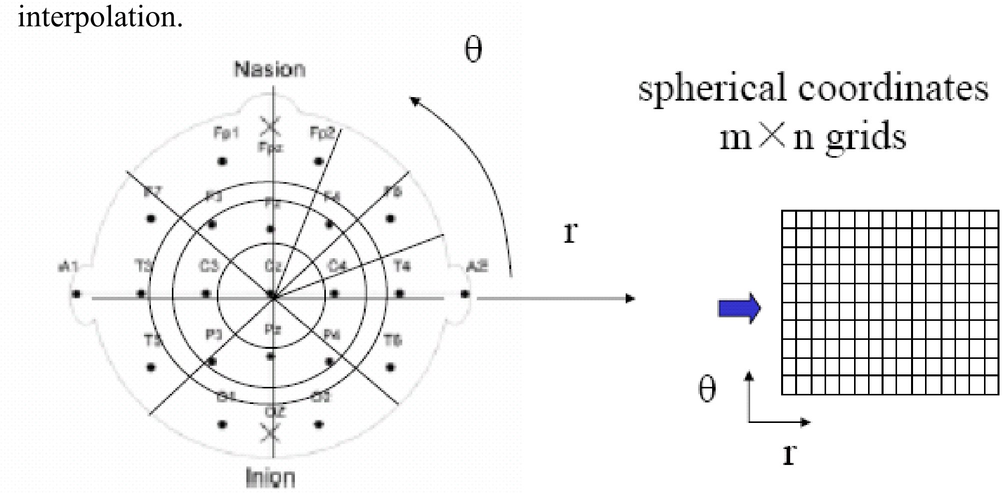
Figure 3.3 Independent Component Analysis

3.3 Scalp EEG Mapping

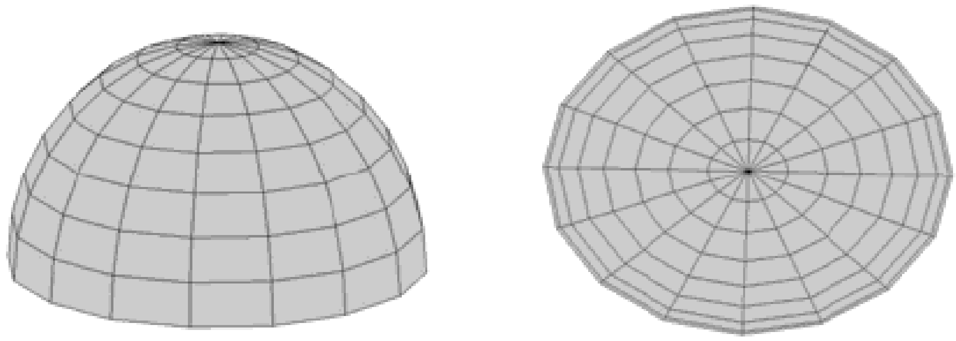
After independent component analysis, the artifacts and noises can be easily identified, such as in Figure 3.3 (b), the heartbeat (C1) and the environment noise (C3) can be removed directly. For other components, such as C4, C5 and C6, it is very difficult to identify the brain activity from them. In order to classify all these components, Scalp EEG mapping is introduced to visualize all the components. There are four steps in the EEG mapping: grid generation, interpolation, equivalence contour calculation and color bar scaling.

3.3.1 Grid generation

In order to represent the power distribution on a coordinator system independent of the electrode position systems, a grid of spherical coordinator system (Figure 3.4) is used. Select proper m and n, all electrodes of international 10-20 system will coincide with grid points; it will help to improve the accuracy of interpolation. And the power distribution is represented by the power values at the grid points. The power value at each grid is determined from the power values of neighboring electrodes by interpolation.



(a) Spherical Coordinator system



(b) Generated grid

Figure 3.4 Grid generation

3.3.2 Interpolation

Generally, linear interpolation is adopted to calculate the grid value. Each grid value is determined by the neighboring electrodes. Figure 3.5 shows the example of linear interpolation.

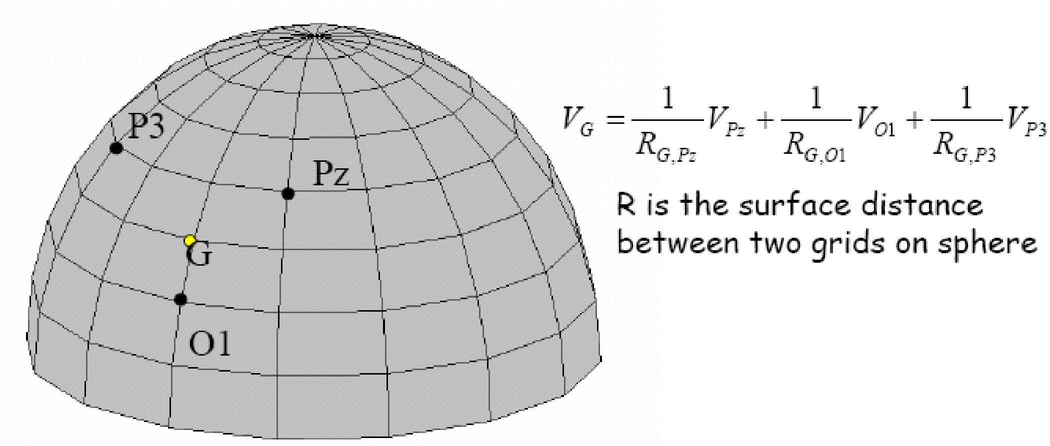


Figure 3.5 Illustration of linear interpolation

3.3.3 Equivalent contour calculation

After interpolation, the value of every grid in the spherical coordinator system has been calculated and compared. Thus, equivalent contour can be drawn. (Figure 3.6)

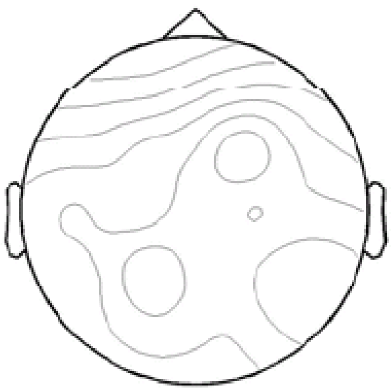


Figure 3.6 Illustration of equivalent contour

3.3.4 Color bar scaling

Self-scale method has been adopted to determine the color value of the equivalent contour. In this method, every independent component's coefficient values in all the electrode position are compared and the color value is determined according to the scaling algorism. (Figure 3.7) After color scaling, the equivalent contour become colored. Figure 3.8 is one example of scalp EEG map, which indicates a special activation pattern in left anterior temporal region.

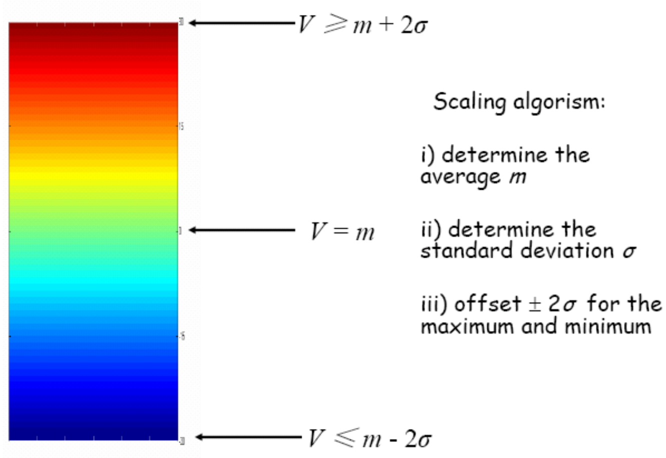


Figure 3.7 Color scaling algorism

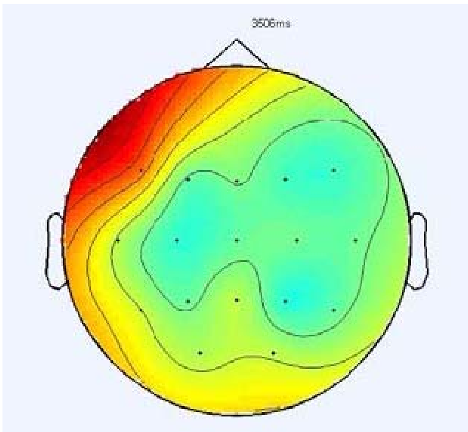


Figure 3.8 Example of Scalp EEG map

3.4 ICA-based EEG Energy Spectrum

For Scalp EEG maps of ICA result, it can be both 2D scalp EEG map and 3D scalp EEG map. (Figure 3.9) So after ICA and scalp EEG mapping, all the independent components can be compared with each other according to their activation pattern.

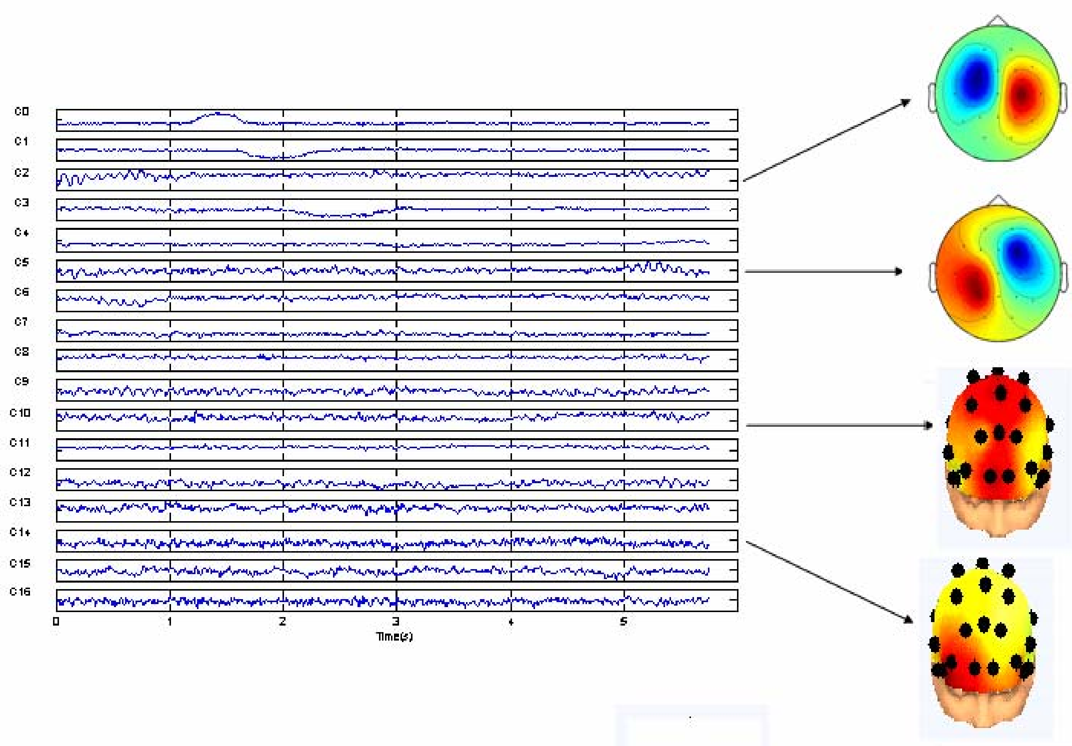


Figure 3.9 Scalp EEG mapping for the ICA results

Furthermore, in order to investigate the brain activation pattern in detailed, 3D scalp EEG mapping for one independent component was computed in four directions: top-frontal, top-behind, top-left and top-right. (Figure 3.10)

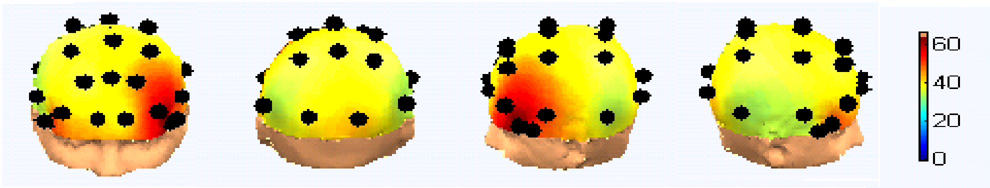
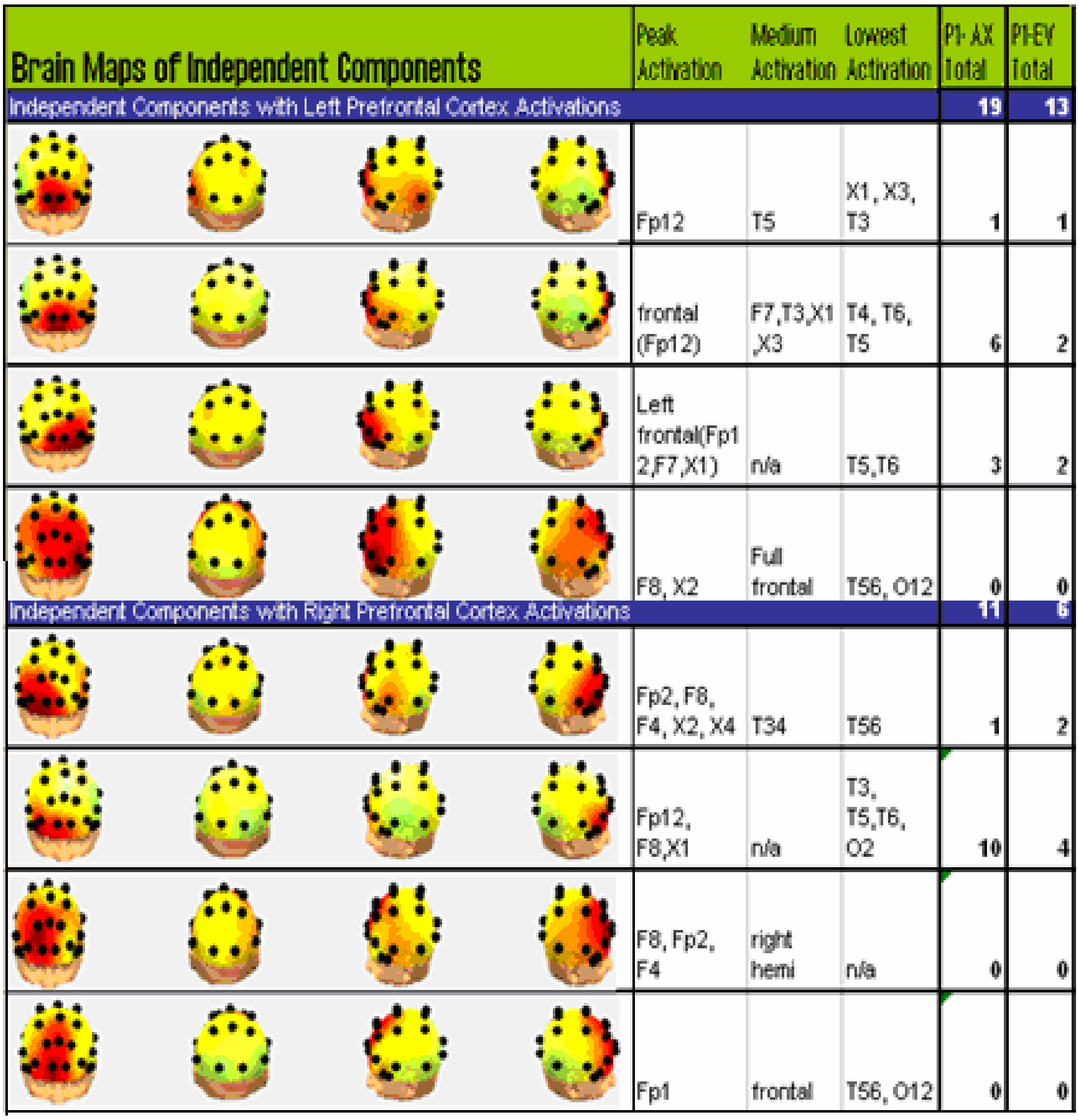


Figure 3.10 Four direction view of 3D scalp EEG mapping for the ICA result



Brain Maps of Independent Components	Peak Activation	Medium Activation	Lowest Activation	PI-AX Total	PI-EV Total
Independent Components with Left Prefrontal Cortex Activations				19	13
	Fp12	T5	X1, X3, T3	1	1
	frontal (Fp12)	F7,T3,X1 ,X3	T4, T6, T5	6	2
	Left frontal(Fp12,F7,X1)	n/a	T5,T6	3	2
	F8, X2	Full frontal	T56, O12	0	0
Independent Components with Right Prefrontal Cortex Activations				11	6
	Fp2, F8, F4, X2, X4	T34	T56	1	2
	Fp12, F8,X1	n/a	T3, T5,T6, O2	10	4
	F8, Fp2, F4	right hemi	n/a	0	0
	Fp1	frontal	T56, O12	0	0

Figure 3.11 classification of 3D scalp EEG mapping for the ICA results

After EEG scalp EEG mapping for all the independent components, we can define several activation pattern labels, such as Left Prefrontal Cortex Activation, Right Prefrontal Cortex Activation, and so on. And all the independent components will be classified into these labels. (Figure 3.11 shows the example of classification of 3D scalp EEG mapping for the ICA results)

After classification, the peak activation points in each independent component in specific scalp region can be summarized according to the classification. This summarized point is the Energy Spectrum. Let’s take the example of Left Prefrontal Energy Spectrum. From the brain structure and international 10-20 system, the left prefrontal region covers Fp1 and F7. So the definition of Left Prefrontal Energy Spectrum is the following:

Left Prefrontal Energy Spectrum (LPES) is the total number of activation points in all independent components which have peak activation in Fp1 or F7. In order words, independent components with peak activations at Fp1 or F7 would be considered to have left prefrontal cortex activation. In such cases, for every independent component which has activation in Fp1 or F7, the data tally for Left Prefrontal Energy Spectrum for that participant would be increased by one if only Fp1 or F7 has the peak activation and would be increased by two if both Fp1 and F7 have the peak activation. For the example showed in Figure 3.10, the LPES is 1 because only F7 is the peak activation.

To sum up, Scalp EEG relates to the energy of neuronal activation in the brain. ICA gives independent components which are associated with specific neuronal activation sources. From the scalp EEG mapping of each independent component, the peak electrical activation in the specific area indicates that the neurons in that region are activated. Thus, the summarized peak electrical points in a specific scalp region from all the independent components will indicate the energy of the neuron group's activation nearby that region.

4 EXPERIMENTAL DESIGN

The overall objective of this research is to propose and develop a new physical quantity for the features in identifying subtle changes in the EEG signal in relationship to negative emotions. In last chapter, the basis and principle of this quantity has been discussed. Thus, this chapter will describe the experimental design for negative emotion detection by using this quantity. Figure 4.1 shows the overall flowchart of the experiment.

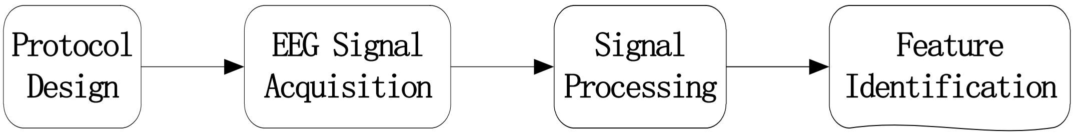


Figure 4.1 Flowchart of the whole project

In this chapter, the biological basis of emotion for the experiments, experiment protocol design, the experiment materials, signal processing method and results verification method used for this research will be discussed.

4.1 Biological Basis of Emotion

From biological aspect, the structures in the human brain involved in emotion, motivation, and emotional association with memory belong to the limbic system, which influences the formation of memory by integrating emotional states with stored memories of physical sensations.

The French physician Paul Broca first called this part of the brain "le grand lobe limbique" in 1878, but its putative role in emotion was not largely developed until 1937, when the American physician James Papez first described his anatomical model of emotion, which is still referred to as the Papez circuit. Papez's ideas were, in turn, later expanded on by Paul D. MacLean to include additional structures in a more dispersed "limbic system," more on the lines of the system described above. The concept of the limbic system has since been further expanded and developed by Nauta, Heimer and others.

4.1.1 Emotion Loop

In 1937, the neuroanatomist James Papez (Papez 1937) would demonstrate that emotion is not a function of any specific brain center but of a circuit that involves four basic structures, interconnected through several nervous bundles: the hypothalamus with its mamillary bodies, the anterior thalamic nucleus, the cingulate gyrus and the hippocampus. Papez believed that the experience of emotion was primarily determined by the cingulate cortex and, secondly, by other cortical areas. Emotional expression was thought to be governed by the hypothalamus. The cingulate gyrus projects to the hippocampus and the hippocampus projects to the hypothalamus by way of the bundle of axons called fornix. Hypothalamic impulses reach the cortex via relay in the anterior thalamic nuclei. This circuit (Papez circuit), acting in a harmonic fashion, is responsible for the central functions of emotion (affect), as well as for its peripheral expressions (symptoms). In 1949, Paul McLean completed and corrected Papez's ideas, and called the larger complex the limbic system, which is what we call it today (Maclean 1952). It included the hypothalamus, the hippocampus, and the amygdala, and is tightly connected with the cingulate gyrus, the ventral tegmental area of the brain stem, the septum, and the prefrontal gyrus. Figure 4.2 shows the basic structure of limbic system.

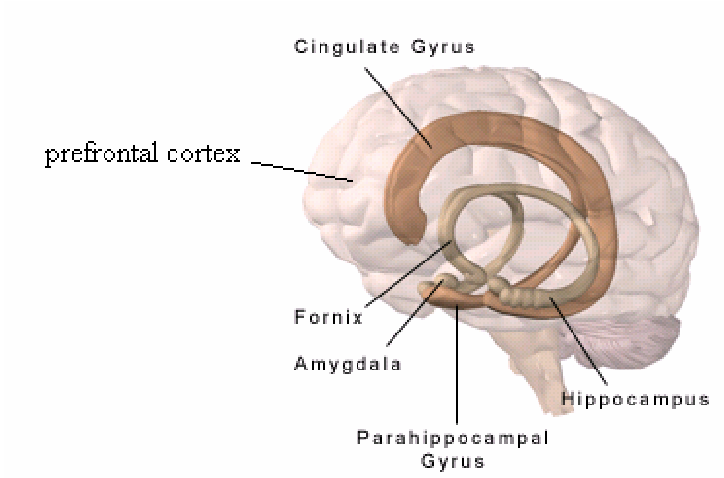


Figure 4.2 Limbic system

4.1.2 Function of limbic system

By influencing the endocrine system and the autonomic nervous system, the limbic system is highly interconnected with a structure known as the nucleus accumbens, commonly called the brain's pleasure center. The nucleus accumbens plays a role in sexual arousal and the "high" derived from certain recreational drugs. These responses are heavily modulated by dopaminergic projections from the limbic system. In 1954, Olds and Milner found that rats with metal electrodes implanted into their nucleus accumbens would repeatedly press a lever activating this region, and would do so in preference to eating and drinking, eventually dying of exhaustion (Olds 1954).

The limbic system is also tightly connected to the prefrontal cortex. Some scientists contend that this connection is related to the pleasure obtained from solving problems. To cure severe emotional disorders, this connection was sometimes surgically severed, a procedure of psychosurgery, called a prefrontal lobotomy (this is actually a misnomer). Patients who underwent this procedure often became passive and lacked all motivations.

There is circumstantial evidence that the limbic system also provides a custodial function for the maintenance of a healthy conscious state of mind. For each component in limbic system, the detailed functions are listed in Table 4.1. (Lautin 2001)

Table 4.1 Function of components of limbic system

Structure	Function
Amygdala	Involved in aggression, jealousy, and fear
Cingulate gyrus	Autonomic functions regulating heart rate and blood pressure as well as cognitive and attention processing
Fornicate gyrus	Region encompassing the cingulate , hippocampus , and parahippocampal gyrus
Hippocampus	Required for the formation of long-term memories
Hypothalamus	Regulates the autonomic nervous system via hormone production and release. Affects and regulates blood pressure, heart rate, hunger, thirst, sexual arousal, and the sleep/wake cycle
Mammillary body	Important for the formation of memory
Nucleus accumbens	Involved in reward, pleasure, and addiction
Orbitofrontal cortex	Required for decision making
Parahippocampal gyrus	Plays a role in the formation of spatial memory

4.1.3 Key components of limbic system

With recent advances in functional brain imaging (fMRI and PET), the circuitry underlying emotion in the human brain can now be studied with unprecedented precision. Two basic systems (approach system and withdrawal system) mediating different forms of motivation and emotion has been proposed (Lang 1990; Gray 1994; Davidson 1995). Although the descriptors chosen by different investigators vary and the specifics of the proposed anatomical circuitry are presented in varying levels of detail, the essential characteristics of each system are similar across conceptualizations. The approach system facilitates appetitive behavior and generates certain types of positive affect that are approach-related, for example, enthusiasm, pride, etc. This form of positive emotion is usually generated in the context of moving toward a desired goal. There appears to be a second system concerned with the neural implementation of withdrawal. This system facilitates the withdrawal of an individual from sources of aversive stimulation and generates certain forms of negative emotion that are withdrawal-related. For example, both fear and disgust are associated with increasing the distance between the organism and a source of aversive stimulation. A variety of evidence drawn from multiple sources suggests the view that the systems that support these forms of positive and negative emotion are implemented in partially separable neural circuits. Recent studies have shown that amygdale and prefrontal cortex (PFC) are key structures in the circuit that govern positive and negative affect (Davidson 1992; Coleman-Mesches K 1995; Zald DH 1997; Zald DH 1998).

A large corpus of data at both the animal and human levels implicates various sectors of the PFC in emotion. The PFC is the anterior part of the frontal lobes of the brain, and is lying in front of the motor and premotor areas. Cytoarchitectonically, it is defined by the presence of an internal granular layer IV (in contrast to the agranular premotor cortex). This brain region has been implicated in Executive Function, which includes planning complex cognitive behaviors, personality expression, moderating correct social behavior, and the abilities to differentiate between conflicting thoughts, determine good and bad, better and best, same and different, future consequences of current activities, working toward a defined goal, prediction of outcomes, expectation based on actions, and so on.

The amygdale is a brain structure that is essential for decoding emotions, and in particular stimuli that are threatening to the organism. When the brain receives a sensory stimulus indicating a danger, it is routed first to the sensory thalamus. From there, the information is sent out over two parallel pathways: the thalamo-amygdala pathway (the “short route”), which is fast, but involuntary and imprecise route, and the thalamo-cortico-amygdala pathway (the “long route”), which is slow, but voluntary and precise route.(Kandel E. R. 2000; Maren 2001)

The short route conveys a fast, rough impression of the situation, because it is a sub-cortical pathway in which no cognition is involved. This pathway activates the amygdala which, through its central nucleus, generates emotional responses before any perceptual integration has even occurred and before the mind can form a complete representation of the stimulus. This route is important because it lets us start preparing for a potential danger before we even know exactly what it is. In some situations, these precious fractions of a second can mean the difference between life and death.

The long route conveys the information from the sensory thalamus to the cortex. First, the various modalities of the perceived object are processed by the primary sensory cortex. Then the unimodal associative cortex provides the amygdala with a representation of the object. At an even higher level of analysis, the polymodal associative cortex conceptualizes the object and also informs the amygdala about it. This elaborate representation of the object is then compared with the contents of explicit memory by means of the hippocampus, which also communicates closely with the amygdala. After processing, the information will reach amygdale again and tell the amygdale whether or not the stimulus represents a real threat. (Figure 4.3)

The imminent presence of a danger then performs the task of activating the amygdala, whose discharge patterns in turn activate the efferent structures responsible for physical manifestations of fear, such as increased heart rate and blood pressure, sweaty hands, dry mouth, and tense muscles.

Based on the above discussion, there are several locations for emotion measurement by EEG, where to collect the emotion related EEG signal will be discussed in the following section.

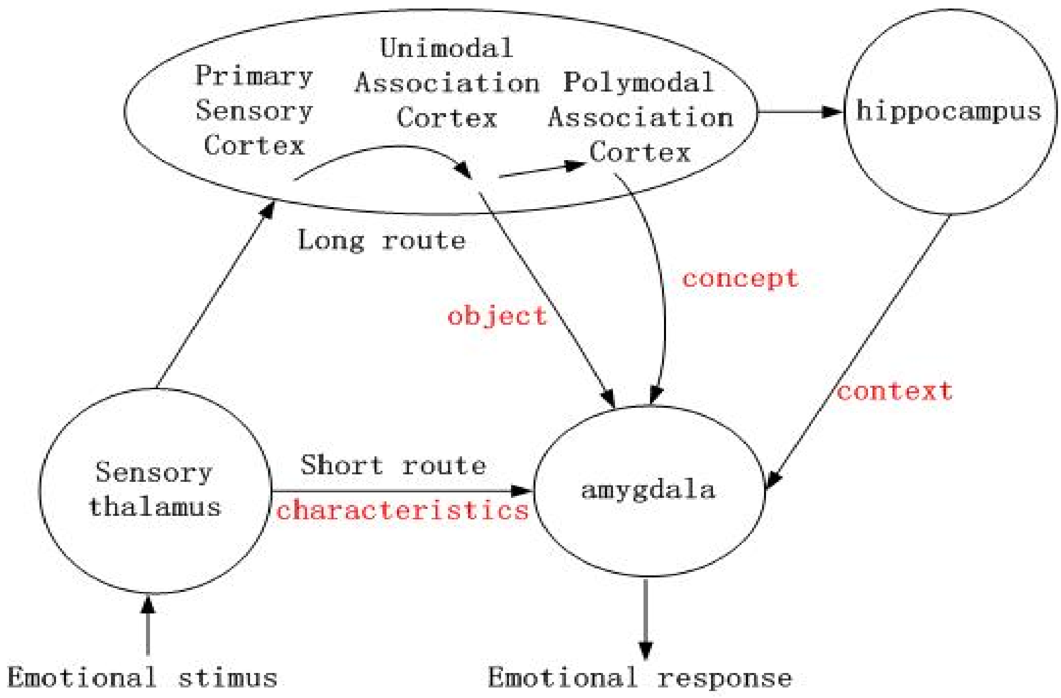


Figure 4.3 Two routes of emotion

4.2 EEG Electrode Placements

In this research, the EEG electrode placement is based on international 10-20 system. However, the brain structure which is involved in the limbic system (Figure 4.4) has two suitable locations, one of which is the temporal pole which belongs to paralimbic system and also connects to Amygdala and hippocampus group. The other location is the prefrontal lobe.

Based on the brain bone and muscle structure (Figure 4.5) and the conductivity (S/m) of body tissues below 100 Hz at body temperature (Table 4.2), the prefrontal lobe can not be a suitable location to detect emotion by using EEG because of two reasons.

One is that the prefrontal bone is thicker than other head bones and also the bone has the lowest conductance. The other reason is that the prefrontal region has more complex higher function, thus it is difficulty to differentiate emotion related EEG signal from other type of EEG signal.

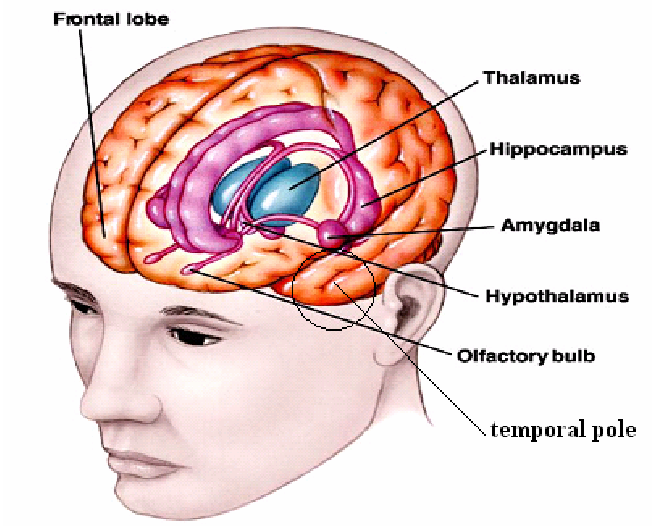


Figure 4.4 Limbic System

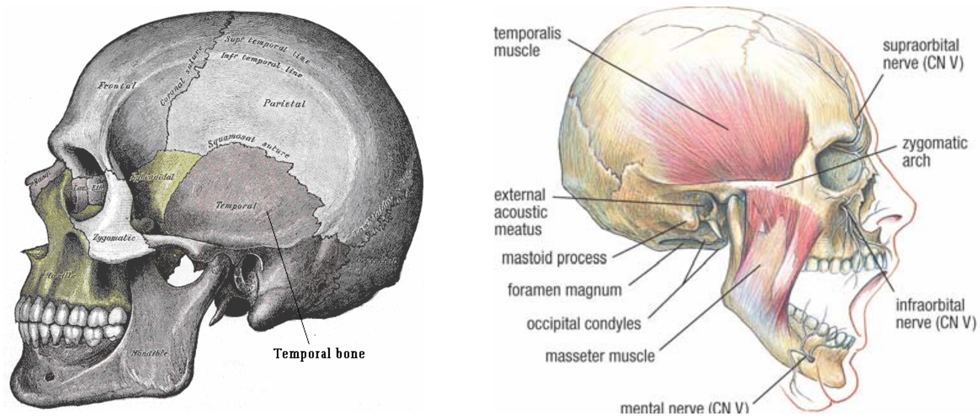


Figure 4.5 Brain Bone and Muscle Structure

So the temporal pole will be considered in this study. Moreover there are some fMRI evidences to support that when the subjects are in the negative emotion states, such as anxiety, there are neurons activation in the anterior temporal region or temporal pole. (Figure 4.6) So four electrodes, X1, X2, X3 and X4, are adopted to collect EEG signal from the temporal pole (Figure 4.7)

Table 4.2 The conductivity (S/m) of tissues below 100 Hz at body temperature

Tissue	Human body	Tissue	Human body
Bone -Marrow	0.05	Cerebellum	0.1
Cartilage	0.18	Colon	0.1
Fat	0.04	White Matter	0.06
Muscle	0.35	Grey Matter	0.1
Blood	0.7	Bone -Cortical	0.02

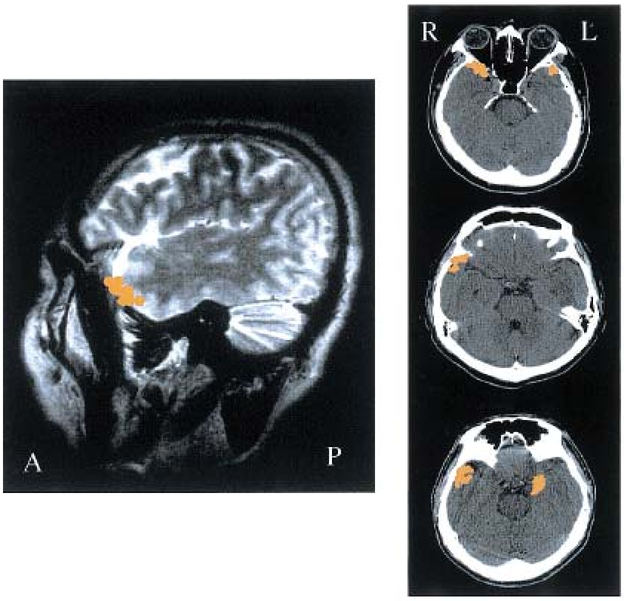


Figure 4.6 fMRI result of anterior temporal region

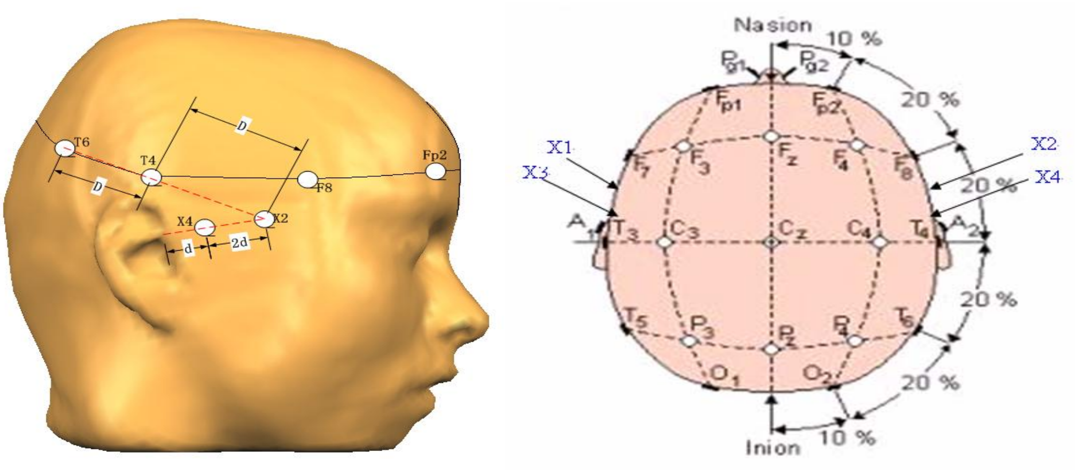


Figure 4.7 Electrode Placement

(a) Right side view of the electrode placement. (b) Top view of the electrode placement. X1, X2, X3 and X4 are four additional electrodes which are the sites on the scalp close to the anterior temporal region and are not covered by the international 10-20 electrode placement system. X1 and X3 are on the left hemisphere and X2 and X4 are on the right side of the head. X2 is attached to the elongating line of T6 and T4, and the distance between T6 and T4 is the same as the distance between T4 and X2. X4 is attached just above the zygomatic process, posterior to the temples by approximately 2/3 of the total length from the temple to the ear.

4.3 Experimental Protocol

How to induce the participants to produce the emotion naturally in the laboratory environment is a key factor for emotion detection. There are several different methods to induce emotions in the laboratory setting. Some research group uses free recall e.g. to ask the participant to relive a situation where they felt anger (Frijda 1989; Mauro 1992). Other stimulus includes videos or computer games like X-quest (van Reekum 2004) and GAME (Kaiser 1996). In this research, several different types of stimulus, such as International Affective Picture System (IAPS), electrical shocks, have been used to induce the participants to produce different type emotions.

4.3.1 International Affective Picture System (IAPS)

IAPS is one of the most widely used emotion stimulus, which consists of over 940 standardized static pictures (Lang 1988; Lang 2005). They are classified with two main rating categories – Valence and Arousal. Valence rating measures the degree of pleasantness and arousal rating measures the intensity of activation. Valence and activation are two separate and orthogonal characteristics of emotion. These ratings are highly correlated between the participants and are verified several times. The rating ranges from 1 (low) – 9 (high). For example, picture of a baby or a couple hugging is of high valence i.e. pleasant pictures; picture of mushroom or stool is of neutral valence i.e. neutral pictures and low valence or unpleasant pictures are pictures of violence or burnt victims.

Large literature has shown that IAPS is reliable in inducing emotions. (Müller 1999) IAPS are also used in research for self reported emotion (Davis 1995), effects on corrugator muscle activity, skin conductance responses and heart rate (Bradley 2001) as well as effects of the IAPS on the rating of affective words (Lang 1998)

In this experiment, the slideshows will present each IAPS picture for 6 seconds with the exception of the emotion control stage with a 5 seconds starting slide. This is a general common procedure for the use of IAPS in research. The slideshow didn't have any indication of the emotion they will induce, this is to avoid demand characteristics and minimize anticipation of the pictures. Also, erotic images were left out of the slides as there could be complications of different emotion induced among males and females (Bradley 2001).

4.3.2 Electrical shocks

Another stimulus used in this experiment was the electric shock device. The mechanism in the lighter which produce a small spark was used to produce a harmless stimulus to the participants (Figure 4.8). It is imperative that the shock device can produce a sharp and painful shock as it acts as a punishment for them to induce anxiety.

Figure 4.8 Mild electric shock device taken from a lighter

4.3.3 Overview Protocol

The whole experiment involves 4 main stages -

I) Positive/pleasant Emotions (PE)

II) Neutral Emotions (NE)

III) Negative/unpleasant emotion (UE)

IV) Anxiety (AX)

The sequence of the experiment is designed to stimulate positive emotions before negative emotions as it is believed that physiological activities due to negative emotions persist longer than positive emotions (Thayerb 2003). The experiment sequence and the approximated time taken for each stage are summarized in Figure 4.9.

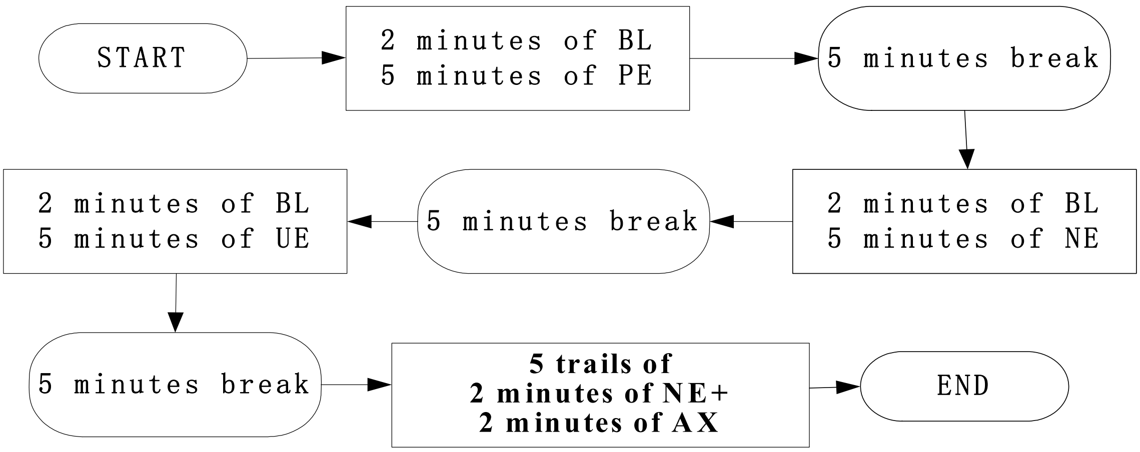


Figure 4.9 Experiment sequence

One experiment lasts approximately 2 hours including the setup time of the EEG system. Each stage is conducted one after another with 5 minutes break in between. This break is necessary for the participant to rest and recover from the stimulus in the previous stage. The experiment is recorded using a video camera to help to synchronize the extraction of the EEG data. Segments of raw EEG data are extracted by checking the facial expression and the body language of the participant in the video.

For the first 3 stages, the stimuli used are series of IAPS pictures. These pictures are shown, with the lights switched off, using a 17 inch color monitor placed approximately 0.5m away from the participant. The participant is isolated to one corner of the room with the experimenter standing behind to minimize any form of contact. This will help the participant to concentrate on performing the experiment. He/she is reminded to pay attention to the slideshows and keep their eyes open during each of stage. At the start of each stage, 2 minutes of baseline (BL) data is taken for comparison. The first two stages, PE and NE, are the two controls for the experiment. The pictures chosen will induce positive emotions and neutral emotions respectively. The third stage, UE, subjects the participant to unpleasant emotions. In the final stage, the participants are required to mentally calculate mathematical for 2 minutes when Neutral Emotion State EEG data will be colleted. After that, the participant will be told that the electrical shocks will be randomly delivered on the left or right hand sometimes. At the same time, the Anxiety related EEG signal will be collected.

4.3.4 Detailed Protocol

Stage I – Positive Emotion (PE)

In this stage, 2 minutes of baseline (BL) are first recorded. The participant will be asked to look at the blank screen. After which, the slideshow will be played and participant will be asked to view the slideshow.

The slideshow consists of pictures are selected from IAPS. They are of high valence rating (M_{val} $\cong$ 7.5) and moderate-high arousal rating ($M_{aro} \cong$ 5.3). The slideshow is 5 minutes long and has 50 pictures. Each picture is shown continuously for 6 seconds. After the slideshow ended, participant will be told to rest for 5minutes

Stage II –Neutral Emotion (NE)

Similar to Stage I, 2 minutes of baseline (BL) are first recorded. The participant will be asked to look at the blank screen. After which, the slideshow will be played and participant will be asked to view the slideshow.

The slideshow consists of pictures are selected from IAPS. They are of moderate valence rating (M_{val} $\cong$ 5.2) and low arousal rating ($M_{aro} \cong$ 2.8). The slideshow is 5 minutes long and has 50 pictures. Each picture is shown continuously for 6 seconds. After the slideshow ended, participant will be told to rest for 5minutes

Stage III –Unpleasant Emotion (UE)

Similar to Stage I and II, 2 minutes of baseline (BL) are first recorded. The participant will be asked to look at the blank screen. After which, the slideshow will be played and participant will be asked to view the slideshow.

Pictures are selected from IAPS. They are of low valence rating ($M_{valence}$ $\cong$ 1.9) and moderate to high arousal rating ($M_{arousal} \cong$ 6.2). The slideshow is 5 minutes long and has 50 pictures. Each picture is shown continuously for 6 seconds. After the slideshow ended, participant will be told to rest for 5minutes

Stage IV – Anxiety (AX)

In this stage, the participant starts to mentally multiply numbers for two minutes. Neutral Emotion EEG data 1 (termed as NE1) is collected. Then the participants will be told that an electric pulse will be delivered on the left or right hand sometime over the next 2 minutes. Electric shock from a small spark emitter is delivered after 2 minutes. Anxiety Present EEG Data 1 (termed as AX1) is collected. Inform participant that 2 minutes are up and let participant rest for 1 minute and collect the NE2 in another 1 minute when the subject is mentally multiplying numbers. Repeated the above processes, and AX2, NE3, AX3, NE4, AX4, NE5, AX5 are collected.

4.4 Experimental Materials

4.4.1 Experiment Participants

Eight right-handed healthy young adults (age range 19-23) were recruited from the National University of Singapore for the experiment. Prior to this, five pilot experiments with different participants have been used to verify the experimental procedures. Using the Edinburgh Handedness Inventory (Oldfield 1971), they are checked to ensure that they are right hand dominant. Experimental exclusion of left hand dominant participants is due to the different hemispheric specialization of the brain Though it is easier to induce emotions, more particularly negative emotions, in females participants, the experiment will extend this research to males as well. Hence, among the participants, four subjects are males and the rest are females. To qualify for the study, subjects had to have no medical contraindications such as severe concomitant disease, alcoholism, drug abuse, and psychological or intellectual problems likely to limit compliance. Before the experiment, the participants are briefed of the general protocol and they are asked to sign the informed consent. Throughout the session, they are constantly reminded to minimize body movement and remain silent to reduce any noise in the EEG data. Each participant will perform the whole experiment in a single session. This is to minimize any variables, such as the impedance values of the electrodes, if each stage is conducted in separate sessions. After the whole experiment, they will be asked to fill in a subjective rating form.

4.4.2 EEG Machine

The commercial EEG machines "PL-EEG Wavepoint system" (Medtronic, Inc. Denmark) (Figure 4.10) with reusable cup electrodes was used to conduct these experiments. Electrodes were placed using ELEFIX EEG paste and SKINPURE skin preparation gel, both products of NIHON KOHDEN. The EEG machine has a frequency band of 0.1-30Hz, 167 sampling frequency and 30 channel input. During all EEG testing, electrical impedances at all electrode sites were less than 13 KΩ.

Figure 4.10 PL-EEG wavepoint system

4.5 Signal Processing Methods

For each participant, 5 sets of Negative emotion state EEG data (anxiety emotion and unpleasant emotion) and 5 sets of Control Emotion state EEG data (Neutral Emotion) have been collected for the analyzing. The participants are observed carefully for signs of significant distress or hints of anxiety, upon which the time is noted down.

In each of these five sets, twelve seconds of mixed EEG data at which the participant seems to experience the most anxiety or unpleasant, is extracted. It was determined arbitrarily to use twelve seconds for each sampled data because twelve seconds is deemed enough time for a distinct anxiety characteristic to be accentuated, yet not too long a period such that other artifacts becomes apparent.

The fast fixed-point algorithm for independent component analysis (FastICA) in Matlab was invoked to conduct Independent Component Analysis. FastICA is an efficient and popular algorithm for independent component analysis invented by Aapo Hyvärinen at Helsinki University of Technology. The algorithm is based on a fixed-point iteration scheme maximizing non-gaussianity as a measure of statistical independence. It can be also derived as an approximate Newton iteration. FastICA separates the mixed signals into distinct, characteristic components independent of one another.

EEGLab was invoked to create 3D maps of brain activity for every component. Figure 4.11 shows 3D scalp EEG map for one of the 23 independent components' scalp EEG maps for anxiety related EEG signal of Participant 3 (P3).

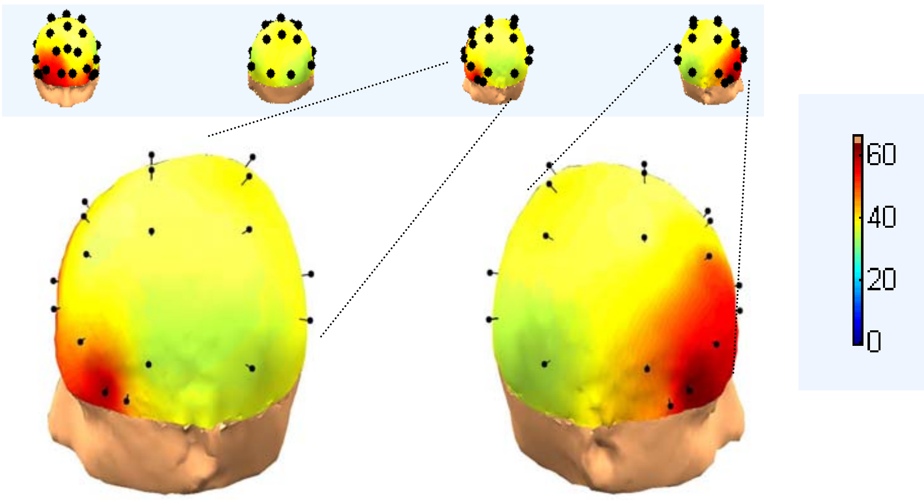


Figure 4.11 3D scalp EEG mapping for independent component of anxiety state related data

Then, ICA-based EEG Energy Spectrum will be used to analyze the experiment results. According to brain structure, biological basis of negative emotion and electrode placement, three types of EEG Energy Spectrum, which are Left Prefrontal Energy Spectrum, Right Prefrontal Energy Spectrum and Anterior Temporal Energy Spectrum, were defined to investigate the possible features of negative emotion measurement by using EEG. The definitions are the following:

Left Prefrontal Energy Spectrum (LPES) is the total number of activation points in all the independent components which have peak activation in Fp1 or F7. In order words, independent components with peak activations at Fp1 or F7 would be considered to have Left Prefrontal cortex activation. In such cases, for every independent component which has activation in Fp1 or F7, the data tally for Left Prefrontal Energy Spectrum for that participant would be increased by one if only Fp1 or F7 has the peak activation and would be increased by two if both Fp1 and F7 have the peak activation.

Right Prefrontal Energy Spectrum (RPES) is the total number of activation points in all the independent components which have peak activation in Fp2 or F8. In order words, independent components with peak activations at Fp2 or F8 would be considered to have Right Prefrontal cortex activation. In such cases, for every independent component which has activation in Fp2 or F8, the data tally for Right Prefrontal Energy Spectrum for that participant would be increased by one if only Fp2 or F8 has the peak activation and would be increased by two if both Fp2 and F8 have the peak activation.

Anterior Temporal Energy Spectrum (ATES) is the total number of activation points in all the independent components which have peak activation in the scalp sites X1, X2, X3, X4, T3 and T4 or any combination of those six sites. In order words, independent components with peak activations at X1, X2, X3, X4, T3 and T4 would be considered to have temporal pole activation. In such cases, for every independent component which has activation in X1, X2, X3, X4, T3 and T4, the data tally for Anterior Temporal Energy Spectrum for that participant would be increased by the number of activation point in these six points.

Because one independent component represent one independent source in the brain in the aspect of EEG and the peak activation area represent the source energy, so the LPES will indicate the left prefrontal cortex activation and the RPES will indicate the right prefrontal cortex activation. Also, the ATES will indicate the temporal pole activation. These three types of ICA-based EEG Energy Spectrum were used to evaluate the negative emotion states, such as anxiety emotion, and the neutral emotion state.

4.6 Support Vector Machine (SVM) Verification

Support Vector Machine (SVM) was used to verify the classable of EEG data between anxiety state and neutral emotion state.

4.6.1 SVM basic algorism

The best word to describe the EEG signal is complex. The EEG complexity originates in the intricate neural system, which is almost a black-box to us. The complexity of EEG signals requires some advanced signal processing methodology prior to any brain activity identification. Therefore, to evaluate the EEG patterns related to different emotion states, a standard artificial learning, two-class Support Vector Machine was used. This machine learning method is widely used for classification (pattern recognition) and regression models, and has been generally believed the best statistical tool for classification and regression.

SVM are learning machines that can perform binary classification (pattern recognition) and real valued function approximation (regression estimation) tasks (Haykin 1999). SVM are generally competitive to (if not better than) Neural Networks or other statistical pattern recognition techniques for solving pattern recognition problems. It is also handy for solving regression problem, which is convenient for continuous tracking fatigue. More importantly, SVM are showing high performance in practical applications in recent studies. Therefore, SVM is chosen to be used in this study. Figure 4.12, 4.13 and 4.14 show the good performance of SVM as a binary classifier.

Consider two classes' training vectors $\mathbf{x}_i \in R^n$, i=1, … , l, and the corresponding target vector $y \in \{-1, 1\}$, SVM solves the following primal problem:

$$\min_{\mathbf{w},b,\xi} \frac{1}{2}\mathbf{w}^T \cdot \mathbf{w} + C\sum_{i=1}^{l} \xi_i$$
$$\text{subject to } y_i(\mathbf{w}^T \cdot \phi(\mathbf{x}_i) + b) + \xi_i \geq 1 \qquad (4.3)$$
$$\xi_i \geq 0, i = 1, 2, ..., l.$$

Its dual is

$$\min_{\boldsymbol{\alpha}} \frac{1}{2}\sum_{i,j=1}^{m} y_i y_j \alpha_i \alpha_j K(\mathbf{x}_i \cdot \mathbf{x}_j) - \sum_{i=1}^{m} \alpha_i$$
$$\text{such that } \sum_{i=1}^{l} y_i \alpha_i = 0 \qquad (4.4)$$
$$0 \leq \alpha_\text{i} \leq \text{C}, \; i = 1, 2, ..., l.$$

The decision function is

$$\text{sgn}(\sum_{i=1}^{l} y_i \alpha_i K(\mathbf{x}_i, \mathbf{x}) + b) \qquad (4.5).$$

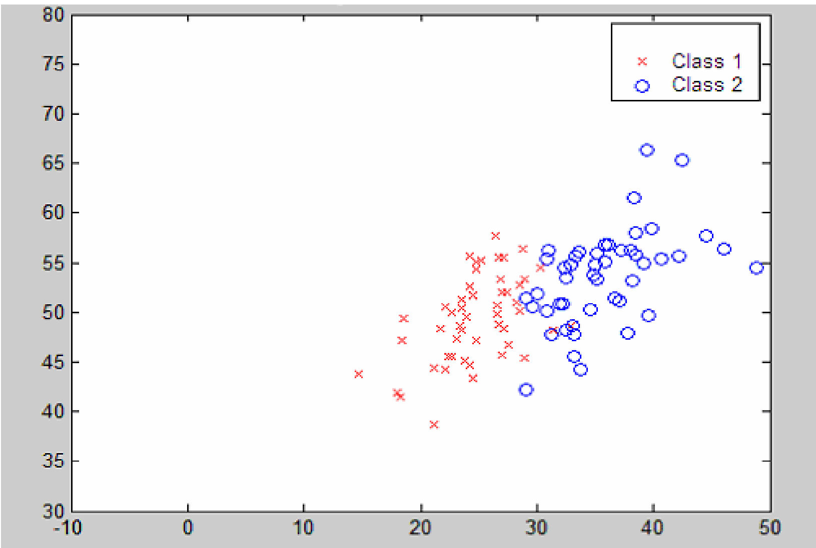


Figure 4.12 Plot of two-class dataset

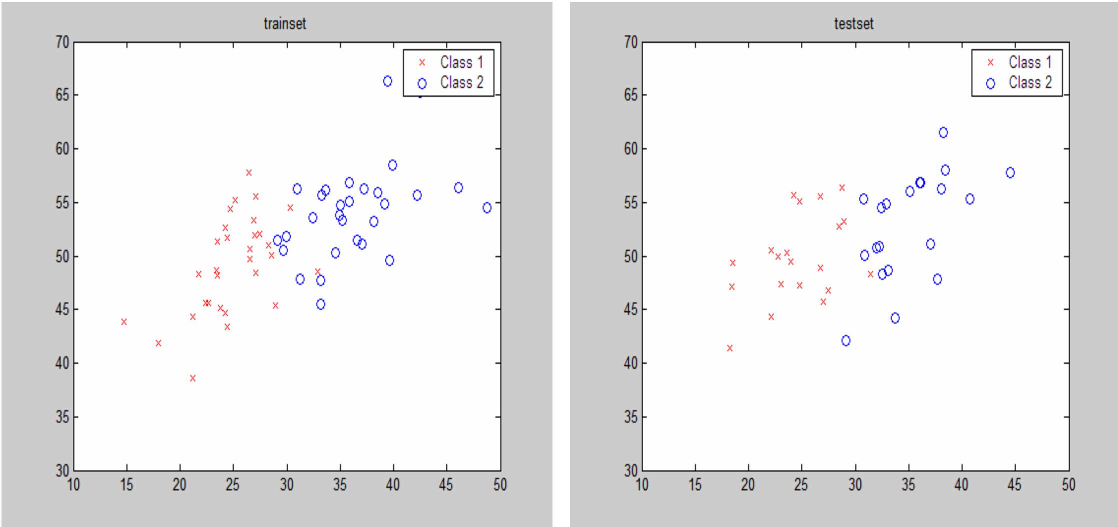


Figure 4.13 Train-set plot and test-set plot

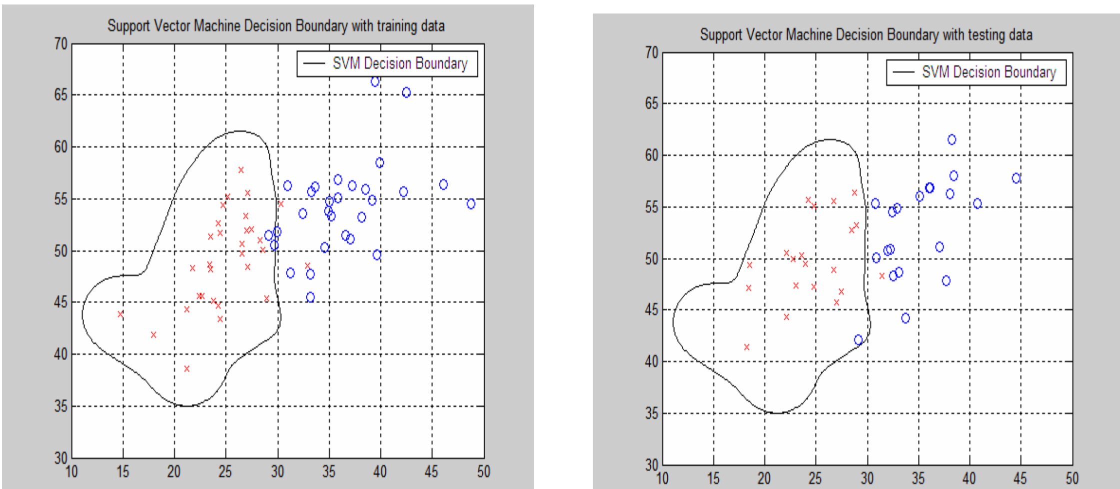


Figure 4.14 Resulting decision boundary of SVM and train-set or test-set data plot

The intuitive way to solve the multi-class classification is "one-against-one" approach. In total of k(k-1)/2 classifiers are actually constructed and each one is trained using data from two different classes. For training data from the ith and the jth classes, the primal problem is:

$$\begin{aligned}
&\min_{\mathbf{w}^{ij},b^{ij},\xi^{ij}} \frac{1}{2}(\mathbf{w}^{ij})^T \cdot \mathbf{w}^{ij} + C\sum_{t=1}^{l}\xi_t^{ij} \\
&\text{subject to } ((\mathbf{w}^{ij})^T \cdot \phi(\mathbf{x_i}) + b^{ij}) \geq 1 - \xi_t^{ij}, \text{ if } \mathbf{x}_t \text{ in the ith class,} \\
&((\mathbf{w}^{ij})^T \cdot \phi(\mathbf{x_i}) + b^{ij}) \leq -1 + \xi_t^{ij}, \text{ if } \mathbf{x}_t \text{ in the jth class} \\
&\xi_t^{ij} \geq 0, t = 1, 2, ..., l.
\end{aligned} \tag{4.6}$$

w = vector of the separating hyperplane which is parameterized by (w,b)

x = position vectors of training data points

Φ = function that maps input space to a high dimensional feature space

ξ = quadratic slack variable added as a measure of error.

C = parameter of trade off between fitting and error tolerance i.e. penalization of the slack variable, ξ.

Since our objective is continuously monitoring emotion, the system's output should be able to track the subtle change of emotion in individuals. Therefore, the pattern recognition should go for regression after essential features in relationship to emotion are validated by means of multi-class classification. Given a set of available samples, $\{(\mathbf{x}_1, z_1), \ldots , (\mathbf{x}_l, z_l)\}$, such that $z_i \in R^1$ is a target value of input $\mathbf{x}_i \in R^n$, the standard form of SVM for regression is:

$$\begin{aligned}
&\min_{\mathbf{w},b,\xi,\xi^*} \frac{1}{2}\mathbf{w}^T \cdot \mathbf{w} + C\sum_{i=1}^{l}\xi_i + C\sum_{i=1}^{l}\xi_i^* \\
&\text{subject to } \mathbf{w}^T \cdot \phi(\mathbf{x_i}) + b - z_i \leq \varepsilon - \xi_i, \\
&z_i - \mathbf{w}^T \cdot \phi(\mathbf{x_i}) - b \leq \varepsilon + \xi_i^*, \\
&\xi_i, \xi_i^* \geq 0, t = 1, 2, ..., l.
\end{aligned} \tag{4.7}$$

The corresponding dual problem is:

$$\min_{\boldsymbol{\alpha},\boldsymbol{\alpha}^*} \frac{1}{2}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*)^T \mathbf{Q}(\boldsymbol{\alpha}-\boldsymbol{\alpha}^*) + \varepsilon \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) + \sum_{i=1}^{l} z_i (\alpha_i - \alpha_i^*)$$
$$\text{subject to } \sum_{i=1}^{l} (\alpha_i - \alpha_i^*) = 0, \tag{4.8}$$
$$0 \le \alpha_{\mathrm{i}}, \alpha_i^* \le \mathrm{C},\ i = 1,2,\ldots,l,$$

where $Q_{ij}=K(\mathbf{x}_i, \mathbf{x}_j)=\phi^T(\mathbf{x}_i)\,\phi(\mathbf{x}_j)$.

The resulting approximate function is:

$$\sum_{i=1}^{l} (-\alpha_i + \alpha_i^*) K(\mathbf{x}_i, \mathbf{x}) + b. \tag{4.9}$$

4.6.2 Data Labeling

Each subjects EEG data were labeled accordingly to the emotion states. In the standard artificial learning, dual-class SVM was used to evaluate EEG patterns related to the two different classes: Anxiety (AX) and Neutral Emotion (NE) States.

4.6.3 Feature Extraction

A fast Fourier transform (FFT) and Power Spectra Density (PSD) were performed on the EEG data. Four features used were extracted from the power spectrum of the EEG data. The frequency range was separated into four frequency bands, namely Delta (1.5Hz~3.5Hz), Theta (3.5Hz~7.5Hz), Alpha (7.5Hz~12.5Hz) and Beta (12.5Hz~25.0Hz). The four features were intended to characterize the power spectral density of EEG data (Hao 1997). Their detailed definitions were as following:

Feature 1: Dominant frequency

Every peak in the power spectrum corresponded to a peak frequency. The peak here was defined as formed by two points. One of them was within the rising slope and the other was within the falling slope, and they corresponded to amplitudes equal to half the amplitude of the peak. These two frequencies formed a frequency band. This band was called full width half maximum band of the peak. Among all the peaks in a spectrum, the peak with the largest average power in its full width half maximum band was called the dominant peak. The peak frequency corresponded to this dominant peak was defined as dominant frequency. This feature was applied to each frequency band.

Feature 2: Average power on the dominant peak

This was defined as the average power on the full width half maximum band of the dominant peak.

Feature 3: Center of gravity frequencies

This parameter was defined as the frequencies that the power spectrum in the given frequency range concentrate. In other words, we can consider this parameter as given the normalized power spectrum as the probability, the mean of frequency. It was described by the following formula:

$$C = \frac{\sum_i P(f_i) \times f_i}{\sum_i P(f_i)}, \tag{4.10}$$

where $P(f_i)$ is the power at frequency f_i.

Feature 4: Frequency variability

This feature was defined as the standard deviation of frequency given the power spectrum as the probability distribution. It was given in the following formula:

$$D = \left[\frac{\sum_i P(f_i) \times f_i^2 - \frac{\left(\sum_i P(f_i) \times f_i \right)^2}{\sum_i P(f_i)}}{\sum_i P(f_i)} \right]^{\frac{1}{2}}. \tag{4.11}$$

The window used in estimating the power spectrum was 500 samples with the sampling frequency 167 Hz, which was in total 3 seconds. Windows overlapped by the time increment of 5 sample points. The dimension of the feature vector was 4 characteristics×4 frequency bands ×(19+4) channels = 368.

4.6.4 Training and testing SVM model

All the EEG datasets for different subjects and different emotion states were separated equally into two parts, one was for training the SVM model (training data), and the other one was for testing the model (testing data). To achieve less bias, we randomized the datasets for these two parts. The labeled training EEG data were fed into SVM; an optimal C value as shown in Equation (4.6) was achieved. Therefore, a dual-class SVM model was set up. Afterwards using the testing data to verify the model, test accuracy was given as the output.

5 Results and Discussions

5.1 Effectiveness of ICA-based EEG Energy Spectrum

5.1.1 Anterior Temporal Energy Spectrum in negative emotion states vs. neutral emotion state

Firstly, pain-induced anxiety state related EEG data was calculated by the Anterior Temporal Energy Spectrum and compared with the ATES in neutral emotion state. Figure 5.1 shows the ATES comparison between anxiety state and neutral emotion state 1, in which the neutral emotion is induced by mentally mathematical calculation and the anxiety emotion is induced by the electrical shocks. The results showed that the averaged ATES in pain induced Anxiety state is 23.6 while it is 18.8 in Neutral Emotion state 1, which means the averaged ATES in Anxiety State is increased by 25.5 percent in compared with the ATES in Neutral Emotion state 1.

Secondly, International Affective Picture System induced Unpleasant emotion related EEG data was calculated by the Anterior Temporal Energy Spectrum and compared with the ATES in neutral emotion state 2.

Figure 5.2 shows the ATES comparison between unpleasant emotion state and neutral emotion state 2, in which the unpleasant emotion was induced by international affective picture system and the neutral emotion state 2 was the baseline. The results showed that the averaged ATES in IAPS induced negative emotion state is 18.2 while it is 15.2 in neutral emotion state 2, which means the averaged ATES in IAPS induced negative emotion state is increased by 19.7 percent in compared with the ATES in neutral emotion state.

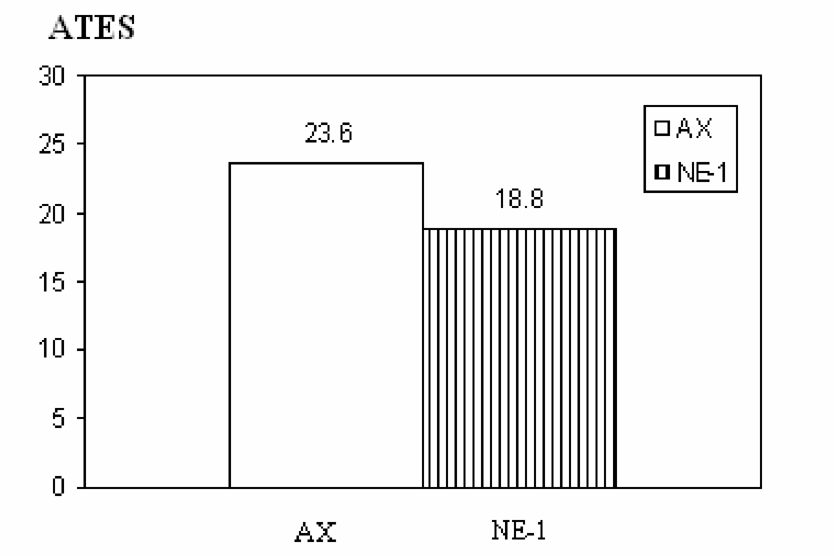


Figure 5.1 ATES comparison between anxiety state and neutral emotion state 1

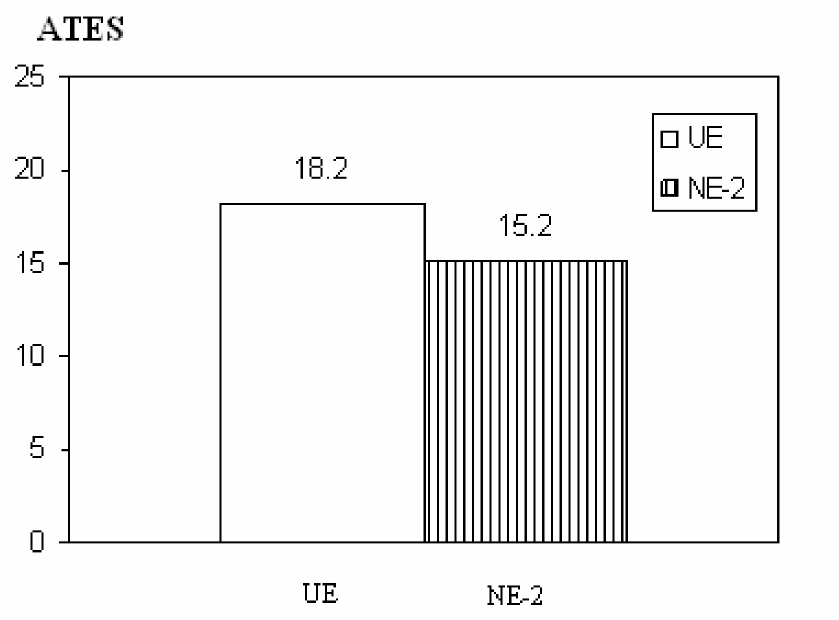


Figure 5.2 ATES comparison between unpleasant emotion state and neutral emotion state 2

However, there is no significant different between the ATES of positive emotion and the ATES of neutral emotion in this research. This may because of the low arousal of positive emotions by the International Affective Picture System or the failure of inducing the positive emotions by the IAPS. This has been confirmed by the questionnaire submitted by the participants after the experiment.

Our results showed that there is an obvious difference in ATES between anxiety state or negative emotion state and neutral emotion state. Reiman et al. reported in a PET study significant blood flow increases in the bilateral temporal poles during the production of anticipatory anxiety (Reiman 1989). Other evidences showed that patients with temporal pole epilepsy experience fear and anxiety, and the temporal pole is associated with panic. Moreover, Yuri Masaoka also confirmed that the temporal pole and Amygdala are associated with human anxiety, which means the neuron groups in the temporal pole and Amygdala will be activated when the subject is in anxiety state. (Masaoka 2000) Thus, negative emotions, such as anxiety, can be considered as the result of sub-neuron groups' activation of temporal pole and Amygdala, which will appear in peak electrical potentials at specific locations on the scalp. By counting the number of these peak electrical potentials, the intensity of neuron activation of temporal pole and Amygdala can be determined. This forms the principle of the anterior temporal Energy Spectrum of anxiety.

From the brain anatomy, the anterior temporal region is the one which covers the temporal pole and Amygdala. So the ATES was calculated and the result is consistent with all literatures results, indicates that negative emotions, especially anxiety, causes discernible differences in EEG data and these differences are detectable using EEG.

Furthermore, the ATES in the pain-induced anxiety is larger than ATES in the IAPS-induced negative emotion, for which one of the possible reasons is the low arousal of emotions by the static pictures system.

5.1.2 Asymmetry of Prefrontal Energy Spectrum in negative emotion states vs. control emotion state

The asymmetry of frontal power spectrum is illustrated by the comparison between the averaged Left and Right Prefrontal Energy Spectrum. Figure 5.3 shows the averaged LFPS in anxiety state is 10.6, in compared with 9.6 in neutral emotion state, while averaged RFPS is 12.6 in anxiety state, in compared with only 8.6 in neutral emotion state, which means the ratio of LFPS and RFPS decrease a lot in anxiety state in compared with in neutral state.

Then, IAPS induced negative emotion related EEG data and neutral emotion related EEG data were analyzed and compared by the Left Prefrontal Energy Spectrum and Right Prefrontal Energy Spectrum.

Figure 5.4 shows the averaged LFPS in unpleasant state is 14.6, in compared with 10.8 in neutral emotion state, while averaged RFPS is 18 in anxiety state, in compared with only 13 in neutral emotion state, which means the ratio of LFPS and

RFPS decrease a lot in unpleasant emotion state in compared with in neutral emotion state.

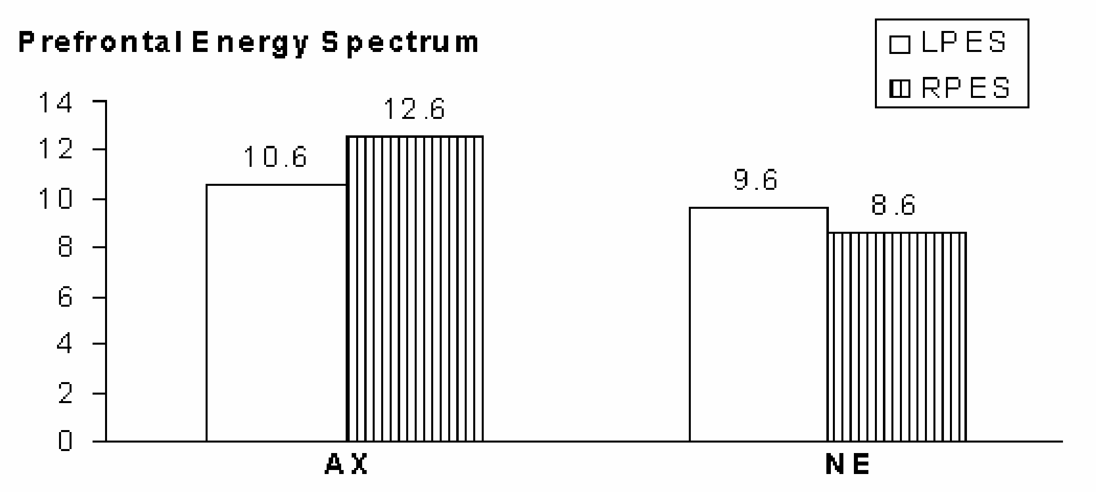


Figure 5.3 Prefrontal Energy Spectrum in anxiety state and neutral state

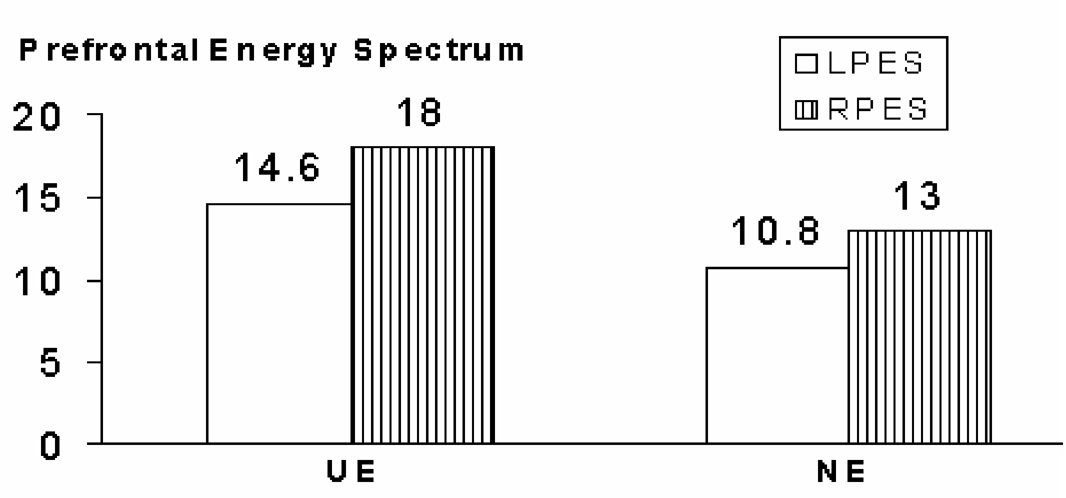


Figure 5.4 Prefrontal Energy Spectrum in negative emotion state and neutral emotion state

Using EEG to study brain asymmetry in humans, researchers have recently made many discoveries suggesting that individual differences in electrical activity between the two brain hemispheres can be used to predict emotional responses to various stimuli. On the basis of a large body of both human and animal studies, Davidson and his colleagues (Davidson 2003) have proposed that greater left-sided dorsolateral activity may be associated with approach-related, goal-directed action planning, whereas on a lesser level of consensus, based on neuron-imaging studies of spatial working memory, they suggested that activation of right lateral prefrontal cortex during withdrawal-related emotion may be associated with threat-related vigilance.

Davidson also reported that positive and negative affective states shift the asymmetry in prefrontal brain electrical activity in lawful ways. For example, film-induced negative affect i.e fear/anxiety increases relative right-sided prefrontal cortex activation, whereas induced positive affect elicits an opposite pattern of asymmetric activation. The results from Figure 5.3 are mostly consistent with Davidson’s findings; with the exception that positive affect was not induced for the current study. For all participants, the percentage of right prefrontal cortex activations in AX averaged 18.8% higher than that of left prefrontal cortex activation, implying that under anxiety states; right prefrontal cortex activity is invariably heightened when compared to the control (NE).

Recent neuron-imaging findings have demonstrated inverse relationships between activity in the Amygdala and regions of prefrontal cortex. One particular study using PET indicated that in normal subjects, glucose metabolism in left medial and lateral PFC is inversely associated with glucose metabolic rate in the Amygdala. It follows that subjects with greater relative right-sided prefrontal metabolism have higher metabolic activity in their Amygdala. Superimposed with findings from the current study it can be inferred that lower ratio of LPES and RPES in AX compared to NE is explained by the positive correlation of right PFC activity with Amygdala activity. Therefore, electrical activity in the right PFC is found to be an indirect measure of the level of activity at the Amygdala. One possible neuron-physiological explanation for this is that the prefrontal cortex has extensive anatomical connections with the limbic structures like the Amygdala. It implies that the Amygdala is indirectly implicated with the prefrontal cortex in this complex neural circuitry of negative affect.

Other findings have supported that the prefrontal cortex is part of a neural mechanism that regulates emotional responses mediated by the Amygdala through conscious evaluation and appraisal. In the pain-induced anxiety stage, participants of the experiment were blindfolded and were unintentionally forced to rely on other cues such as sound and subtle changes in airflow near the skin, to predict when the electric shock would occur. When a cue emerges, the participant may feel a sudden wave of anxiety temporarily. However, the feeling of anxiety dies down upon recognizing that it was a false alarm i.e. the shock did not strike then. The state of anxiety does not persist because there is a cognitive, conscious evaluation of the situation that involves the prefrontal cortex in the neural modulation of negative emotion. Negative emotion regulation is implied only in states of anxiety and not in emotionless or positive affective states because the participant is not experiencing anything negative in the first place. Thus, the results are explained even further by the role in which the prefrontal cortex plays in regulating negative emotional responses from the Amygdala through indirect inhibitory connections.

Collectively, the findings regarding decreased ratio of LPES and RPES in AX compared to NE indicates that EEG can detect anxiety through prefrontal power spectrum. This further substantiates the point that negative emotions, especially anxiety, causes discernible differences in EEG data and these differences are detectable using EEG.

5.1.3 Validation of Experiment design

In our results, the positive emotions induced by IAPS can not be differentiated from baseline or neutral emotions induced by IAPS. This is because of the difficult in inducing positive emotion in the laboratory condition, which has been pointed out in the literatures. And also this has been confirmed by the questionnaire from the participants after the experiments. In the questionnaire, the subjects pointed out that they were experiencing much more in the negative emotion inducing process than in the positive emotion inducing process.

Furthermore, using IAPS to induce negative emotion has been verified by many other researchers, and their results have shown that IAPS has more effect in inducing negative emotions than in inducing positive emotions, which is consistent with our results.

For the pain-induced anxiety, it could be beyond the comprehension of some as to why this study had performed experiments using induced anxiety with pain. Also, some skeptics may argue that the stimulus of this study i.e. anticipating an electrical shock; may not be sufficient to induce a state of anxiety in the study participant.

In a study on anxiety related respiratory potentials, the temporal poles and the Amygdala showed increased levels of oxygen consumption activity when the participants in the experiment were subjected to anxiety inducing stimuli. (Masaoka 2000) The stimulus used in this experiment was an electric pulse that stung the forefinger of each experiment participant. Anxiety was self-reported after the experiment was completed and said to occur during periods where the participants anticipated the electric stimulus (Masaoka 2000). Since both experimental results and self report implicated a state of anxiety, it is with a high degree of certainty that this experimental method was effective for Masaoka's study. As the anxiety inducing methods used in both studies are similar, the experimental data acquired is safely assumed to contain states of anxiety.

Since each participant has five trails to be induced anxiety, the relationship between the induced anxiety and the experiment runs has been investigated. Figure 5.5 shows the trend of the averaged asymmetry of frontal energy spectrum changing with the experiment trails in anxiety state and neutral emotion state.

In Figure 5.5, the ratio of the LPES and RPES in anxiety state increased with the experiment runs. Moreover, the ratio of the LPES and RPES in neutral emotion state is lower than that in anxiety emotion in the first 4 trails, but in the fifth trail, the result is just the opposite. The possible reason is that the participant may become more and more getting used to these electrical shocks, thus the induced effect will be decrease, even there is no anxiety in the fifth trail.

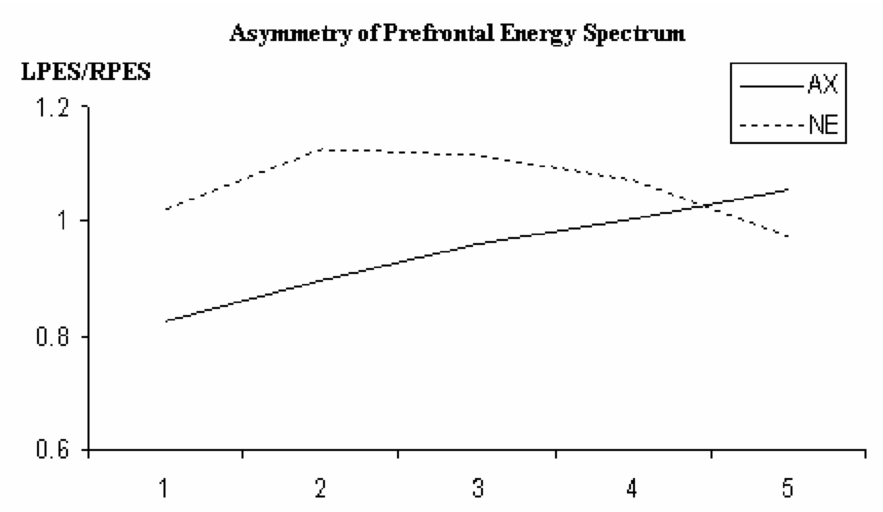


Figure 5.5 Validation of experiment design
The horizontal axis is the experiment trails and the vertical axis is the ratio of LPES and RPES, which indicates the asymmetry of frontal energy spectrum. In this figure, the dotted line represented the asymmetry of frontal energy spectrum in the neutral emotion state, while the real line stood for the asymmetry of frontal energy spectrum in the anxiety state.

For the neutral emotion state, the participant was requested to do the mental mathematical calculation according to the experiment protocol; therefore, the long time mental mathematical calculation could lead the participant to produce some other negative affect, such as slightly dysphoria, slightly depression. All these have been confirmed by the questionnaire for all participants after the experiments. So the experiment should not be repeated too many times on the same participant in one time slot.

5.1.4 SVM Verification of the EEG data

The level of accuracy is calculated to be 86.4% by using default C value of 1.0. As we know, C is a parameter of the trade off between fitting and error tolerance. However, the default value is not the best value to be used during SVM prediction of the two classed (AX and NE). An iterative train and test method that is analogous to "tuning" may be used such that the C parameter is optimized. To achieve this, each raw EEG data set used to train the SVM is trained and tested against the other data sets which are also involved in the SVM training. An optimal C value is obtained through this training, which will result in a heightened accuracy rate when the SVM tests and predicts EEG data as AX or NE. Figure 5.6 shows the results from the optimization of C parameter when testing and training hand-picked values from 2^{-4} to 2^{3}. The C value with the highest accuracy rate is the optimal C value.

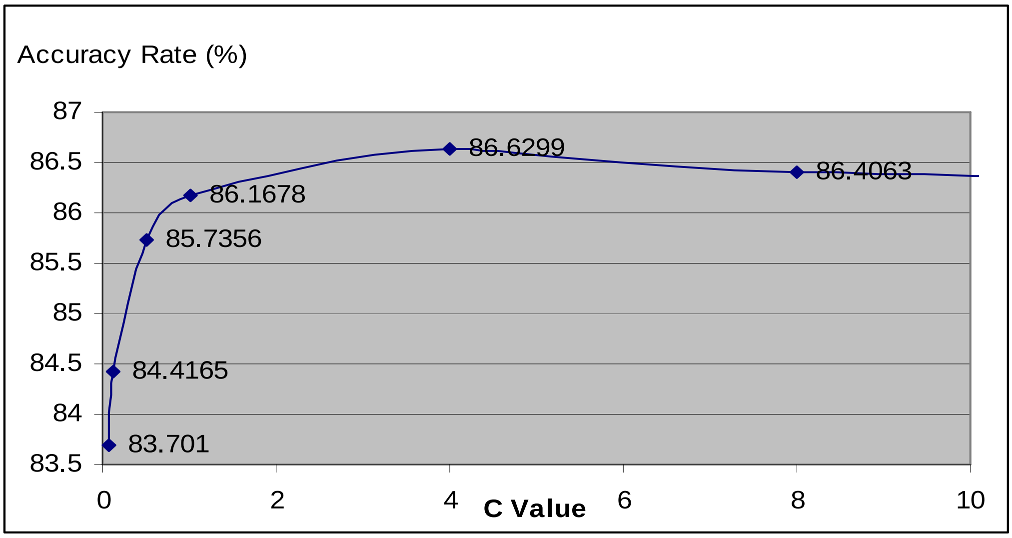


Figure 5.6 Relationship between Training Accuracy Rate and C value of SVM during optimization

The optimal C is found to be C=4.0. Using this new optimal C parameter in the SVM's prediction of EEG data, the results are shown in Table 5.1:

Table 5.1 SVM prediction result with optimal C

Parameter	Value
Accuracy rate	86.9429%
Mean squared error	0.130571
Squared correlation coefficient	0.545955

Therefore, instead of the accuracy rate of 86.4% procured by the default C parameter of 1.0, the optimal C parameter of 4.0 found the accuracy rate to be 86.9%.

The SVM prediction accuracy results show that there are obvious differences between negative emotion state and neutral emotion state in the aspect of EEG data, which have been confirmed by our experiment results.

6 Conclusions

6.1 Conclusions

This study is mainly to develop the novel signal processing methodology and pattern recognition system, which can be used to detect and identify subtle changes in the EEG signal in relationship to negative emotions of individuals through some measurable characteristics.

6.1.1 ICA-based EEG Energy Spectrum has been proposed

- The ICA based EEG energy spectrum at a particular location is defined by the number of ICA components with the peak potential at the location, in which each ICA component corresponds to a specific neuronal activation in the brain.

- The energy spectrum has been applied to the negative emotions, such as anxiety, measurement by counting the energy spectrum at the prefrontal and anterior temporal regions.

- The experimental results showed that the anterior temporal energy spectrum increased significantly and the ratio of right prefrontal energy spectrum to left prefrontal energy spectrum increases significantly from Neutral Emotion mode to Negative Emotion mode.

6.1.2 Negative emotions, especially anxiety, causes discernible differences in EEG data in compared with neutral emotion and these differences are detectable using EEG

- A series experiments have been designed for the negative emotion detection and experiment results have been analyzed by ICA based EEG Energy Spectrum and verified by SVM. The results have shown that the experimental protocol is useful for the negative emotion measurement or detection.

- Negative emotions and neutral emotion have shown significant differences by using ICA based EEG Energy Spectrum analysis, including the anterior temporal energy spectrum and asymmetry of prefrontal energy spectrum.

- The dual-class SVM prediction has achieved very high accuracy, which substantiate that there are obvious differences between negative emotion state and neutral emotion state in the aspect of EEG data

- Our results have shown that one type of specific emotion stimulus should not be put on the subjects for the long time; otherwise, the same stimulus will produce the opposite effect. For example, mental mathematical calculation was designed to induce the neutral emotion, but the long time of mental mathematical calculation would induce the negative emotions, such as abhorring. Also, the fear of pain was designed to induce the negative emotions, such as anxiety, however, the long term of the pain will let the subject get used to this feeling and the induced negative emotion would be weakened.

6.2 Recommendations for Future Work

Although the proposed method has achieved the primary objective of negative emotion measurement using EEG and SVM, improvements can be made to make this method more accurate and reliable. Directions in which this work could be further explored and enhanced are as follows:

1. Further consider and improve the experiment design. Our limitation of this study lies in the emotion stimulus. The positive emotion induced by IAPS was unsuccessful in the experiments. So other types of stimulus for positive emotion should be considered. Also, the stimulus for negative emotion should also be standardized. Such as, the electrical pulse should be exerted by the clinical nerve conduction tester capable of generating mild electrical shock, by which the pain induced anxiety degree can be controllable.

2. Recruit a larger population samples and include wider range. Not all subjects demonstrated the same set of physiological characteristics because of individual differences such as age, gender, or the different ability to control emotion. And the detection and prediction accuracy could be increase when a larger sample of testing data was used. Hence future experimentations should increase the sample size and include a wider range such as age and races.

3. New EEG machine should be used in the future experiments. The new EEG machine should be stable and have large frequency bandwidth. Especially, this new EEG system should have enough input channels for the possible appended electrodes.

4. In this study, only the dual SVM prediction has been conducted, thus in future experiments, the multi emotion states should be considered together and the multi-SVM prediction should be considered.

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