Int. J. Biomedical Engineering and Technology, Vol. X, No. Y, XXXX

Time-frequency analysis of EEG for improved classification of emotion

V. Vanitha and P. Krishnan

National Centre for Sustainable Coastal Management (NCSCM),
Anna University Campus, Chennai, Tamil Nadu, India
Email: vanikkdi@gmail.com
Email: krishnanars@yahoo.com
*Corresponding author [V.Vanitha]

Abstract: Emotion detection has crucial role in many domains especially in health and e-learning sector. This study aims to improve the accuracy in detecting emotions using brain activity. It addresses two primary problems associated with current emotion recognition systems. Firstly, these existing systems can classify only small classes of emotion. Secondly, analysis of the EEG is complex due to its non-stationary and non-linear characteristics. We conducted experiments to record EEG of subjects using 14 electrodes attached directly to the scalp based on International 10-20 system. To remove artefacts, raw signals are pre-processed. Emotional patterns associated with EEG are detected on time-frequency domain using Hilbert–Huang Transform (HHT). Multiclass Support Vector Machine classifier (MC-SVM) is used to distinguish emotions from recorded data based on the instantaneous frequency obtained through HHT. The results revealed the effectiveness of the suggested time-frequency-based analysis method to detect wide range of emotions using EEG signals.

Keywords: emotion recognition; brain–computer interface; EEG; SVM; HHT.

Reference to this paper should be made as follows: Vanitha, V. and Krishnan, P. (XXXX) 'Time-frequency analysis of EEG for improved classification of emotion', *Int. J. Biomedical Engineering and Technology*, Vol. X, No. Y, pp.xxx–xxx.

Biographical notes: **V.Vanitha** is pursuing Doctoral degree in Computer Science and Engineering at Anna University, India. She received her Bachelor's degree in ECE at Madurai Kamaraj University, India and Master's degree from Teesside University, UK. Her research focuses on Affective computing, Cognitive computing and their integration into E-learning Systems.

Dr. P. Krishnan started his research career as Scientist at Central Island Agricultural Research Institute, Port Blair in 2003 and subsequently moved to National Centre for Sustainable Coastal Management, Chennai in 2013 as a faculty. Currently he is Principal Scientist at National Academy for Agricultural Research Management, Hyderabad, India. He has undertaken research studies on diverse aspects *viz.*, coastal bio-resource conservation, fisheries resource management, aquatic environment and health management, conservation planning and policy, etc. Dr. Krishnan is a recipient of national and regional awards for his research contributions and has special interest in using innovations in teaching and communication.

1 Introduction

Emotion plays a crucial part in everyone's day-to-day activities such as learning, reasoning, decision-making, social activities and communication. Emotional Intelligence (EQ) is the process of recognising, managing and regulating one's own and others emotion (Mayer and Salovey, 1993; Mayer and Geher, 1996). It determines how an individual behaves and competes to reach his goal. Furthermore, it is the foundation for critical abilities needed for attaining success in career and number of studies has shown that top performing professionals and students have high emotional intelligence (Parker et al., 2005; Walker, 2006). EQ is considered more powerful than Intelligent Quotient (IQ) in bringing success to achieve the personal goal. A human generally performs action based on his EQ. One should be conscious about his emotions and need to manage emotions effectively.

Recognition of emotion has potential application in health and educational sectors. The association between and emotion and health dates back to ancient times. It is a determining factor for human health and disease. For instance, positive feeling will help in the speedy recovery of ill people. As the positive mood reduces the stress, it helps to strengthen the immune system. On the other hand, negative emotions increase the risk of several diseases like cardiac arrest. Emotion has a huge part in preserving one's mental health. Hence, it is important to provide advanced techniques that help better understanding of human emotions in many medial scenarios like Borderline Personality Disorder (BPD), Autism, etc. The impact of emotion on learning is evident from several studies carried out in recent times (Yin and Guo, 2010; Guangzuo, 2010). It has potential to influence the learning of the learners, affect their rational thinking and lead to success or failure depending on the emotional state. For example, if a student is in a happy emotional state, his ability to extract knowledge from information raises resulting in achievement of desired goal successfully. If he is in anger or fear state, he will be distracted following in the deterioration of attention towards the goal. He disengages himself from learning leading to frustration. Thus, emotion influences the way students perceive and interpret information and build knowledge. The emotional factor is vital in e-learning due to lack of face-to-face interactions. As learners interact with mouse and keyboard all the time, they tend to lose interest and focus (Juan and Shaoqin, 2006). It is important to consider the emotion of the learners to provide positive learning environment.

As researchers from several domains have acknowledged the role of emotion in human accomplishments, the need for the emotion recognition system has grown. It is a sophisticated problem and poses many challenges due to its multifaceted nature. It is a function of time, space, experience, ethics, and cultural background (Zeng et al., 2009). In last few years, advancements and progress have been made in theories, approaches and methods for emotion recognition, yet it is hugely unexplored.

Emotions have been elicited from various sources like facial expressions (Cohen et al., 2000; Bourel et al., 2002), speech (Schuller et al., 2005; Wang et al., 2015), ECG (Agrafioti et al., 2012), EEG (Lin et al., 2010), physiological signals (Picard et al., 2001) and text (Li and Xu, 2014). However, they are prone to several drawbacks. In the emotion detection using facial expression, one should look at the camera all the time. If he is conscious about it, the authenticity of the expression will be lost (Sebe et al., 2007).

It poses challenges regarding gender, age, facial hairs. Added to that, participants having certain conditions like Parkinson's disease have trouble to express their emotions. Though physiological signals can overcome these challenges, they face other issues. For example, emotion detection using Galvanic Skin Response (GSR) is affected by perspiration due to stress/physical activity. Emotion detection using acoustic features are affected by acoustic variability by gender, speaking style and accent variation due to different ethnic origin. Emotion detection using EEG overcomes the aforementioned issues. In addition to that, psychological studies proved the connectivity between brain and emotion (Damasio et al., 2000). It offers several advantages over other methods due to its invasive nature and low cost.

EEG is the procedure to record wave patterns which occur due to electrical impulse generated by the neuro-chemical activity in the neurons. It is called as 'Window of the mind' as it captures the activity going inside the brain accurately. It is a tool containing rich source of information and provide an insight to understand the ongoing activities of the brain. The limbic system in the brain involves with emotion includes amygdala, thalamus, hypothalamus, and hippocampus (Papez, 1937). As EEG measures of the electrical activities of the brain, it is an excellent tool for emotion elicitation.

In this work, we evaluated the performance of our approach at real time in e-learning setting. Through our experiment, we have established a clear understanding on wide range of emotions by considering both primary and secondary emotions. Furthermore, this framework can be easily fitted to many applications like medical, advertising. The rest of the paper is structured as follows. Section 2 discusses the current evidence available to recognise emotion using EEG signals. Section 3 explains in detail about the time frequency analysis of EEG to extract the Hilbert Spectrum. In addition, it presents the theoretical background about SVM classifier and implementation of multiclass SVM. Section 4 presents the experiments and reveals results obtained with relation to the performance of the proposed system. The final section highlights the conclusion and future work.

2 Related work

Researchers developed methods to elicit emotion from biological signals. They utilised facial expression, ECG, heart rate, speech signals, and physiological signals to detect emotion. They even used the natural language processing techniques to determine the emotion. In emotion detection using EEG technique, different electrode placement positions have been adopted. Traditional 62 electrode placements have been used for providing accuracy. Some researchers reduced the electrodes to 24 channels, 14 channels, nine channels, eight channels to reduce the processing complexity. Different types of stimuli have been used to induce emotion. The stimuli can be music, video, combination of music, and video, International Affective Digital Sounds (IADS), International Affective Picture System (IAPS). Different sets of feature extraction have been extracted from EEG signal to detect emotion. Features can be extracted in Time domain, Frequency domain or Time- Frequency domain. Time domain features include power, mean and standard deviation of the signal, Hjorth features, Fractal Dimension or Higher Order Crossing features. Frequency domain includes feature like Band power, Higher Order Spectra. It can be extracted using Fast Fourier Transform (FFT), Short-time

Fourier Transform (STFT) or Welch density estimate. Time-Frequency analysis includes Hilbert–Huang Transform (HHT) or Discrete Wavelet Transform (DWT).

Several studies have been recorded in literature to detect emotion based on two models.

- Discrete model: According to this model, emotions are categorised into small number but universal emotional states based on evolutionary features. It suggests happiness, anger, surprise, fear, disgust, and sadness are the six basic emotions that a human exhibits. Several extended discrete models have been proposed that differs in number and basic types of emotion.
- Dimensional model: This model abstracts the emotion along two or three dimensions. It assumes that emotions can be represented along two-dimensional planes of valence-arousal. Each emotion is expressed as varying degree of levels along these two planes.

2.1 Discrete emotion model

In Petrantonakis and Hadjileontiadis (2010), a novel tool named HOC-EC for extracting features from EEG was proposed. The oscillatory patterns of EEG signal extracted using Higher Order Crossing (HOC) represented the feature set. They employed four different classifiers to distinguish six basic emotions. SVM classifier produced the maximum classification rate of 83.33%.

Murugappan et al. (2010) distinguished five basic emotions using DWT. EEG data are acquired from 20 participants based on International 10-10 standard. Raw EEG is pre-processed with Surface Laplacian Filter to remove noise. Then db4 wavelet technique is used to separate pre-processed signal into three rhythms of EEG. They computed three features, namely Recoursing Energy Efficiency (REE), Logarithmic REE (LREE) and Absolute Logarithmic REE (ALREE) and applied *K*-Nearest Neighbours and Linear Discriminant Analysis techniques to classify emotions. Maximum classification rate of 83.26% is obtained using *K*NN classifier on ALREE feature set.

2.2 Dimensional emotion model

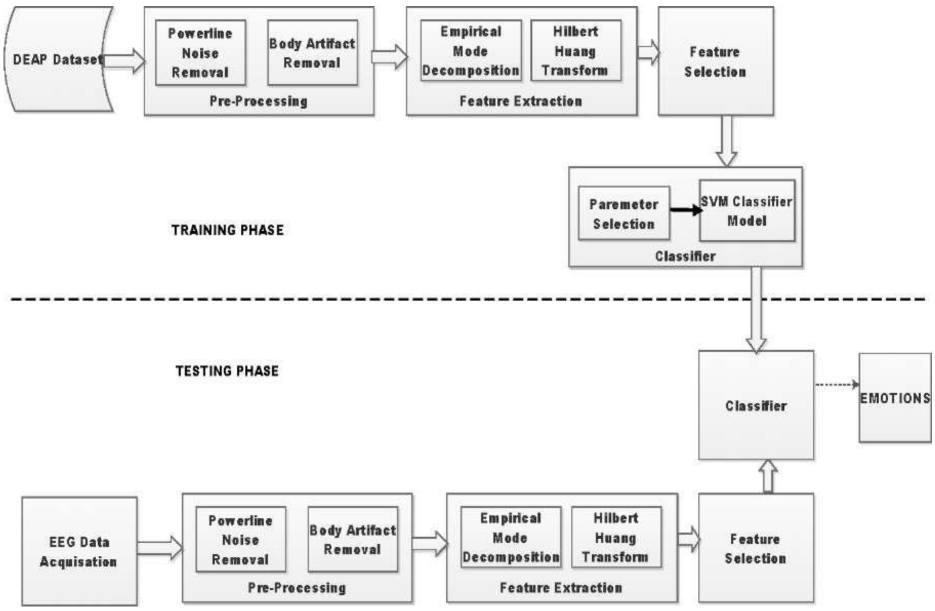
Khosrowabadi et al. (2014) proposed layered neural network for detecting emotion. Discrimination of emotions from EEG is based on two-dimensional valence-arousal model. Neural network is designed with six layers where each layer performed a distinguished function. The classification accuracy is evaluated using SAM responses. The highest classification rate of 62.30% with QDA for single channel and 83.3% is obtained with SVM for combined channels.

Atkinson and Campos (2016) proposed an approach to classify emotional states based on valence-arousal dimensional model. They combined mRMR feature selection approach with classifier to improve accuracy. Experiments are conducted on DEAP data set and results are compared for different feature selection techniques like GA-SVM. The accuracy achieved in the experiment is not published to the best of our knowledge but authors claimed that the proposed approach is superior to many existing approaches.

3 Proposed methodology for emotion detection

Emotion detection from EEG presents many challenges. The non-linear and non-stationary nature exhibited by EEG adds complexity to the feature extraction process. In addition, they are heavily contaminated by noises from power line and artefacts from body movements. In our work, we addressed these issues by using appropriate approach. This work unearths the relation between emotion and EEG by (i) extracting time-frequency specific features using HHT, (ii) using advanced artefact removal method to improve signal to noise ratio, and (iii) evaluating efficacy of SVM classifier with different kernel functions. Figure 1 depicts the proposed system with training and testing phases. Following section explains the data acquisition, time-frequency domain feature extraction and classification of emotion in detail.

Figure 1 Proposed emotion recognition system



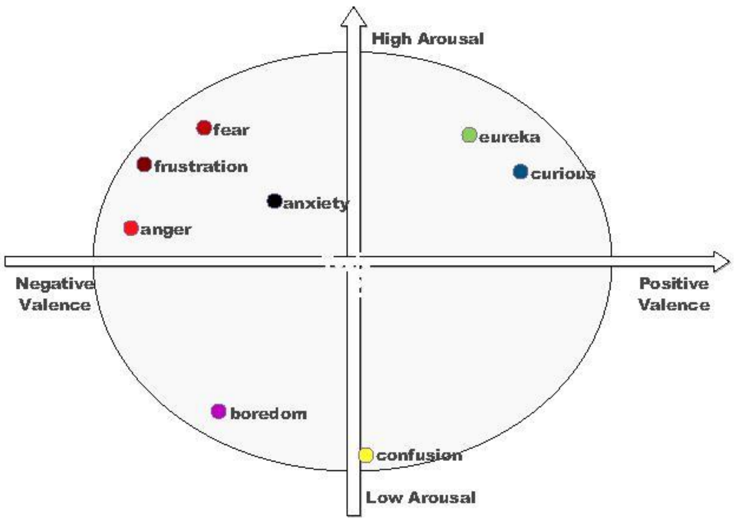
The objective of the study is to capture wide range of emotions with high accuracy. The number and variation of emotions exhibits by human remains controversial. In this study, we chose key emotions of online learners identified in other researches (Schaller et al., 2002; Wegerif, 1998; Ng, 2001; Noriko and Kling, 2003). The frequently occurring e-learning emotions that are considered for this study are fear, frustration, confusion, anxiety, anger, boredom, curious, and eureka. The selected academic emotions in context with learning are summarised in Table 1.

These emotions can be represented along two-dimensional planes of valence-arousal model. The horizontal plane represents valence (quality) ranging from pleasant to unpleasant and the other plane represents arousal (activation) varying from calm to excite. Figure 2 shows the plot of these emotions at various positions in valence-arousal model.

Table 1 Academic emotions

Emotions	*Indicators*
Anger	Antagonism and strong displeasure.
Anxiety	Feeling uneasy about technology, lack of social contact.
Boredom	Lack of interest, lack of face contact.
Confusion	Sense of doubt, unclear and uncertain about concepts.
Curious	Desire to learn.
Eureka	Clear goals, goal of reaching success.
Fear	Freezing due to failure and frightened due to isolation.
Frustration	Dissatisfaction due to structure and design of e-contents.

Figure 2 Representation of academic emotions in valence-arousal model (see online version for colours)



3.1 Pre-processing

As EEG has very small amplitude, it can be easily contaminated with various forms and sources of noise. The noises in EEG called artefacts mainly arise from body movements (EMG), eye movements (ocular artefacts) and power line. For proper analysis, these artefacts have to be removed from original EEG signal, but at the same time without losing valuable information present in original signal. The raw EEG signals undergo the following pre-processing steps to eliminate noise.

- Power line noise removal: EEG signals contain power line inference of 50–60 Hz. A combination of 0.75 Hz high pass and 45 Hz Finite impulse Response (FIR) filter was used to filter out the noise.
- Ocular artefact removal: The useful EEG signal for emotion lies in the frequency range of 0.3 Hz to 44 Hz. The ocular artefact occurs at 0.1–16 Hz. To preserve the

natural properties and information of EEG, wavelet decomposition approach using bi-orthogonal wavelet bior3.9 was employed. The contaminated signal $F(n)$ is expressed as:

$$F(n) = U(n) + N(n) \tag{1}$$

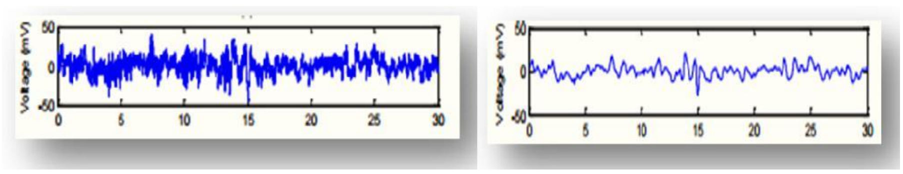
$U(n)$ is useful signal and $N(n)$ is noise.

De-noising method involves the following steps:

1. Decompose the contaminated EEG signal to four levels with bior3.9 wavelet.
2. Define a threshold value. Apply soft threshold to shrink the wavelet coefficients.
3. Apply Inverse DWT to reconstruct the noiseless signal.

Figure 3 (a) and (b) shows raw and de-noised EEG signals, respectively.

Figure 3 (a) Raw EEG with noise, (b) de-noised EEG using bior3.9 (see online version for colours)



(a) (b)

3.2 *Feature extraction in time-frequency domain*

Numerous techniques based either on time or on frequency analysis have been employed for extracting relevant features from EEG. However, these approaches are not appropriate for the EEG signals as they are non-stationary and non-linear in nature. Applying the linear approach for a non-linear signal, results in the extraction of limited amount of information. In order to consider the non- linear dynamics, we have implemented HHT, an adaptive technique to analyse EEG data in time-frequency domain. In addition to that, this approach does not demand prior knowledge and information about EEG. HHT was performed in two steps to extract instantaneous frequency as discussed below.

Step 1: Decomposition: Smaller sets of Intrinsic Mode Functions (IMF) are obtained by decomposing pre-processed EEG signal.

Step 2: Hilbert Transform: Instantaneous frequency is extracted for each IMF component by applying Hilbert Transform on it.

3.2.1 *EEG decomposition using EMD*

IMF components obtained through the decomposition of the pre-processed signal has to satisfy two fundamental conditions and stated as given in Huang et al. (1998).

Condition 1: The number of extrema and zero crossing must either be equal or differ by one.

Condition 2: At an instance, mean value of the envelope defined by maxima and minima should be zero. The decomposition process is iterative and terminates when the residual signal becomes monotonic in nature. Let $X(t)$ be the EEG signal. The decomposition process for $X(t)$ is described below.

Mean value computation

1 Construct a lower ($e_{min}(t)$) and a upper envelope ($e_{max}(t)$) using cubic spline method by identifying lower maxima and upper maxima of the pre-processed signal, respectively.

2 Compute the mean for envelope as:

$$m_{10}(t) = \left[e_{min}(t) + e_{max}(t)\right]/2 \tag{2}$$

Shifting process

3 Obtain first proto IMF component ($h_1(t)$) by subtracting mean from original signal.

$$h_1(t) = X(t) - m_{10}(t) \tag{3}$$

4 Let $X(t) = h_1(t)$. Iterate through steps 1–3 until signal converges. The first decomposed component $c_1(t)$ is:

$$c_1(t) = h_{1k}(t) \tag{4}$$

5 Calculate first residual component ($r_1(t)$) as per equation given below.

$$r_1(t) = X(t) - c_1(t) \tag{5}$$

6 Now $r_1(t)$ becomes parent signal. Repeat steps 1–5 to calculate

$r_2(t)$. *IMF computation*

7 Repeat the entire procedure from steps 1–6 until $r_n(t)$ becomes constant or meets stopping criteria. $X(t)$ is sum of extracted IMF components and residual signal and expressed as:

$$X(t) = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{6}$$

Figure 4 shows first eight IMF components obtained when EMD is applied on EEG signal. Finite number of IMF components that can be extracted through this method depends on the nature of original signal and the stopping criteria. The instantaneous amplitude of the IMF components shown in Figure 4 revealed that strength of the oscillation decreases for higher order of components. Also it is evident that EMD separates the higher frequency components during initial decomposition and lower frequency components in the subsequent decomposition.

3.2.2 Instantaneous frequency using Hilbert transform

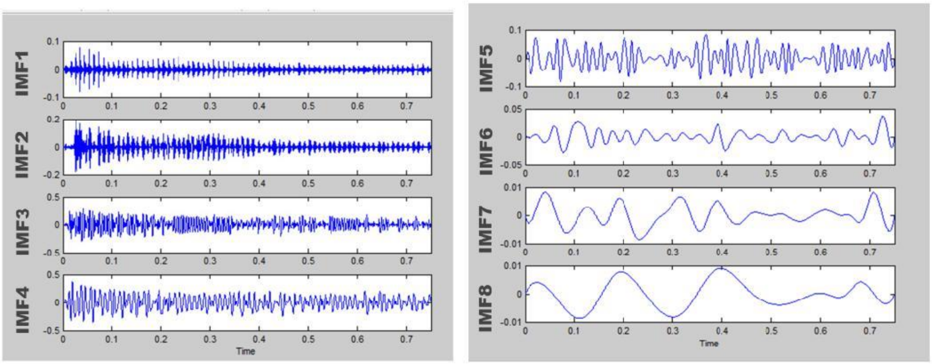
In this step, Hilbert spectrum is computed for each $c_j(t)$ obtained in the previous step. For each IMF, Hilbert transform is applied as given in equation below.

$$H\left[c_j(t)\right] = \frac{1}{\pi} P.V \int_{-\infty}^{+\infty} \frac{c_j(t)}{t-\tau} \partial\tau \tag{7}$$

where H[.] is Hilbert transform and P.V indicates Cauchy Principal value. The instantaneous frequency is computed as:

$$\omega(t) = \frac{1}{2\pi}\frac{\partial \theta_j(t)}{\partial t} \quad \text{and} \quad \theta_j(t) = \arctan\left(H\left[c_j(t)\right] / c_j(t)\right) \tag{8}$$

Figure 4 Eight IMF components obtained through EMD process (see online version for colours)



3.2.3 Separation of EEG sub-bands

The five primary sub-bands of the EEG signals called rhythms are involved in the recognition of emotion. They fall in the frequency ranging between 0 Hz to 50 Hz. The characteristics of primary EEG rhythms are shown in Table 2. The EEG rhythms are separated based on the frequency of the individual IMF components. The instantaneous frequency for each rhythm is calculated which is used as feature vector for classification.

Table 2 EEG rhythm characteristics

Sub-band	*Freq (Hz)*	*Location*	*AMP (mV)*	*Activity*
Delta	0–4	Thalamus	20–200	Deep sleep.
Theta	4–7	Hippocampus, Cortex	20–100	Creativity, intuition.
Alpha	8–13	Posterior regions, occipital lobe, cortex	20–60	Relaxation
Beta	13–30	Cortex	2–20	Memory, problem-solving.
Gamma	30–100	Cortex	20–70	Cognition, information processing, learning, perception.
Noise	>100			

3.3 Classification

We chose Multiclass Support Vector Machine (MC-SVM) for classification due to its insensitivity to over-fitting problem and ability for high generalisation. It is widely implemented in many complex real-world problems such as face recognition, handwriting recognition, and intrusion detection. SVM provides better accuracy for even smaller set of training samples and outperforms conventional supervised classifier.

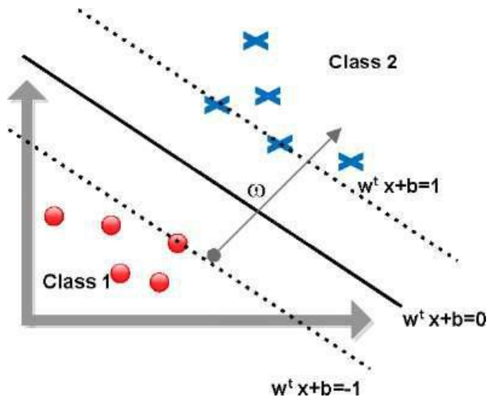
3.3.1 Basic principle

It is rooted on the principle of hyper-planes that determines the decision plane in the input vector space. It searches for the best divider plane to maximise the separation among target classes. The hyper-plane that separates the target classes is constructed from training samples. The trained model is then used to predict classes for the test data samples.

3.3.2 Linear separable SVM

In a binary classification problem, consider *N* training sets having tuple x_i, y_i where $I = 1, 2, \ldots, n$. For the training sample, input data vector is given as $x_i = (x_{1i}, \ldots, x_{ni})$ and output as y_i $\{-1, 1\}$.

Figure 5 Linear separable SVM classifier (see online version for colours)



The hyper-plane that maximises the separation of binary classes is given as:

$$y(x) = \omega^t x + b \tag{9}$$

where *w* is weight vector, *x* is the input vector and *b* is bias.

There are number of possible linear separators, but SVM chooses the one that is maximally distant from data vectors in target classes. The idea behind is that small number of training samples called support vectors are utilised to find the decision plane. For a linearly separable data set, decision plane classifies the data s.t:

$$\omega_0^T x_i + b_0 = 1 \qquad if \quad y_i = +1 \tag{10}$$

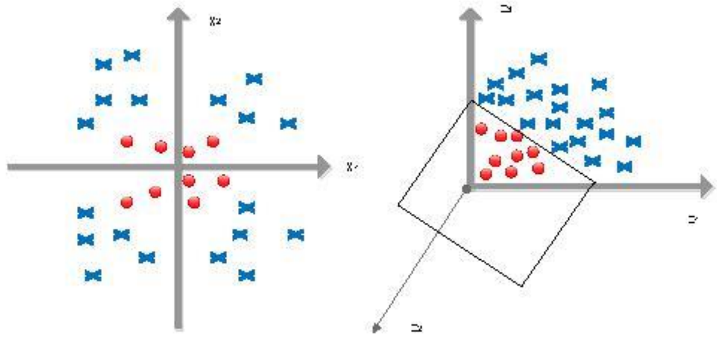
$$\omega_0^T x_i + b_0 - 1 \qquad if \quad y_i = -1 \tag{11}$$

Figure 5 depicts an SVM linear model with decision plane (solid line) and two support vectors (dotted line).

3.3.3 Non-linear SVM

As SVM is a linear classifier, it does not suit for many real applications. When the classes are not separable by a linear plane, kernel function is implemented. The role of kernel function is to obtain linear separable plane by projecting the input vector onto a higher dimensional space. The transformation of non-linear separable problem into linear separable is illustrated in Figure 6.

Figure 6 Mapping of input data to higher dimension using kernel transfer function (see online version for colours)



For the training data set:

$$D = X_1, X_2, \ , X_N \big| X_i \in R^d \ for \ i = 1, 2, \ , N$$

Class label for the binary target is expressed as:

$$y \in \{0,1\}$$

The hyper-plane that maximises the separation of binary classes is given as:

$$y(x) = \omega^t \phi(x) + b \tag{12}$$

Here, φ is a kernel function and is represented as:

$$\phi(x_i, x_j) = \phi(x_i)(x_j) \tag{13}$$

3.3.4 Multiclass SVM

Though SVM is initially designed as binary classifier, it can be extended to classify multiple classes. Complex problem is divided into a set of binary classification problems. There are few commonly used approaches for solving multiclass problem using SVM: (i) One against One, (ii) One against All, and (iii) Directed Acyclic Graph (DAG).

One against one approach

One against One combined was adopted for classification of emotions. This method constructs C(C- 1)/2 classifiers for C classes. Each input samples from two classes are used to train the SVM classifier, thus evaluating all possible pairwise combinations. Each SVM classifier is trained with examples of the first and second class as positive and negative examples, respectively. The decision of each classifier is combined using Max-Wins algorithm. It has efficient computational time as the number of training sample is smaller for each classifier.

For a multiclass problem, the training set has N samples where $x = x_1, x_2 \ldots, x_i$ is the input vector and $i = 1,2, \ldots, n$.

Target class is represented as:

$$yi \in \{1, 2, \; C\}$$

The decision hyper-plane is expressed as:

$$f(x) = argmax_c \left\lceil \omega_b{}^T x + b_c \right\rfloor \quad for\ c = 1,2 \; C \tag{14}$$

The final classifier is given as:

$$f(x) = \sum{}_i x_i{}^T + b_c \tag{15}$$

When the model is applied to test data, each classifier would give one vote to the winning class. The test data are labelled with the class that obtained the most winning votes.

Training MC-SVM

The DEAP data set (Koelstra et al., 2012) is used for training the classifier. It contains EEG signals from 32 subjects recorded while watching videos. The recording was done using 32 channels as per standard 10-20 International system. Data set obtained from the experiments conducted for this study was also added to training set. We extracted features from these signal using time-frequency analysis approach and fed to SVM for training along with the target class. A model constructed during this phase is used for testing phase. SVM with three different kernel functions (linear, polynomial, RBF) was implemented. The parameters of the classifier and kernel function were selected using cross-validation method. The performance comparison is discussed in the next section.

4 Experimental design

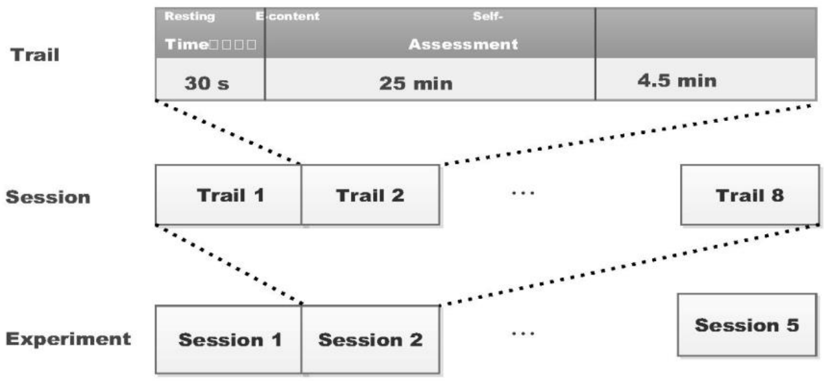
To understand the association between EEG and emotion, various factors have been intensively investigated along three perspectives:

- Number of electrodes.
- Types of kernel function.
- Different parameter setting for each kernel function.

4.1 Data acquisition protocol

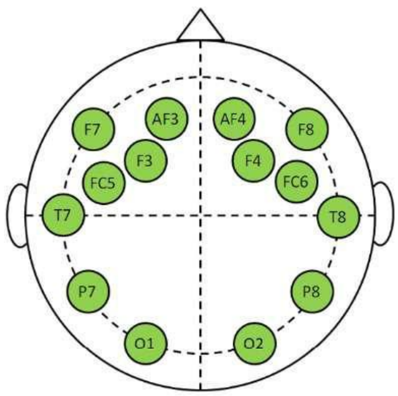
The experiment is conducted in a natural setting. Pilot study is done with six postgraduate students (five men, one woman). They are all healthy subjects and do not have any neurological disorders or psychiatry problems. E-learning materials with varying difficulty level displayed through e-learning system are used as stimuli. The materials are designed by subject experts in a way that it invokes inference, reasoning, analysis, and thinking skills. During the procedure participants study each e-learning topics displayed to them through e-learning system. They completely focused on their study for entire session. We conducted sessions each lasting for 30 minutes and eight trails per session. They are also requested to provide self-report on the emotions experienced for each topic. Each trail consists of e-content inducing same emotion to insure the stability of the emotional state over certain period of time. The protocol for experiment is depicted in Figure 7. Through this procedure we recorded the emotional state of the learners during learning when exposed to various emotional stimuli.

Figure 7 Protocol for EEG data collection



EEG recording were carried out using EMOTIV EPOC headset. It is a wireless device with 14 channels for data acquisition and two channels for reference. The electrodes were placed as suggested in International 10-20 system. Figure 8 indicates location of 14 electrodes (excluding reference electrodes) on the scalp.

Figure 8 Electrode placement (see online version for colours)



Source: EMOTIV EPOC neuro headset

To minimise the power line noise, electrode impedance was below 5 KΩ. The acquired data are digitalised at 12 bit and sampling rate was fixed at 128 Hz for each channel.

4.2 Channel selection and reduction

In the studies (Rizon et al., 2008; Zheng and Lu, 2015) it is observed that Beta and Gamma sub-bands are closely associated with emotion processing. Based on these observations, nine channels are selected (T7, T8, TP7, TP8, FP1, PZ, FP2, FT7 and FT8). There are several advantages associated with electrode reduction. Firstly, number features will reduce and hence lower the computational complexity. Secondly certain channels are very irrelevant to detect emotion (Nie et al., 2011) which increases the complexity of the process including performance degradation, decrease SNR and increase computational cost. As EMOTIV EEG headset does not support above placements, a 64 channel EEG cap is used.

4.3 Classification set-up

We conducted experiments using three different kernel functions and are shown in Table 3. The choice of the kernel depends on the problem as there is no best kernel function according to 'no free lunch theorem'. Yet, choosing appropriate parameters of the kernel plays a crucial role for success of kernel-based classifier algorithms.

Table 3 Properties of three different kernel functions

Kernel function	$\phi\left\{x_i, x_j\right\}$ *for* $\gamma > 0$	*Adjustable parameter*
Linear	$x_i^T.xj + b$	–
Polynomial	$\left(x_i^T.x_j + c\right)^d$	Slope γ, Constant c, Polynomial degree d.
RBF	$\exp\left(-\Vert x_i - x_j\Vert\right)/2^{22}$	$\gamma = 1/2\sigma^2$

The penalty parameter C in SVM classifier and adjustable kernel parameters are set with caution to balance error and model complexity.

- For linear kernel cost parameter is chosen as $C \in \left\{2^{-1}, 2^1, 2^2, 2^3 \quad 2^{15}\right\}$
- For polynomial kernel, $C \in \left\{2^1, 2^2 \quad 2^7\right\}$ and $d \in \left\{5\right\}$.
- *For RBF kernel,* $C \in \left\{2^1, 2^2, 2^3 \quad 2^7\right\}$ *and* $\gamma \in \left\{0.03, 0.05\right\}$.

The next step was to train the MC-SVM for different emotional target classes using DEAP data set and acquired EEG data in this experiment. Owing to small data set constraint, tenfold cross-validation scheme was adopted.

5 Experimental results and discussion

To evaluate the accuracy of the proposed approach, a prototype was developed in MATLAB. Preliminary experiments were conducted by varying kernel parameters to find optimal parameter settings. We conducted two separate experiments to compute classification rate for 14 channel and 9 channel data. For both experiments, classification rate was computed along four quadrants, namely Positive Valence/High Arousal (PV/HA), Positive Valence/Low Arousal (PV/LA), Negative Valence/High Arousal (NV/HA), Negative Valence/Low Arousal (NV/LA). We also evaluated the effect of number of electrodes and their position had on emotion detection.

Experiment 1: Selection of kernel parameters

The experiment was conducted for three different kernels varying their adjustable parameters. The performance of SVM classifier is primarily determined by kernel function which in turn depends on kernel parameter.

As there is no procedure or rule for their selection, we conducted experiments to determine the best possible value for them. Table 4 shows the parameter setting that provided the best classification rate.

Table 4 Optimal kernel parameters settings

Kernel function	*Kernel parameter*	*PV/HA (%)*	*PV/LA (%)*	*NV/HA (%)*	*NV/LA (%)*	*Average accuracy (%)*
Linear	–	67.75	78.4	81.33	57.42	71.225
Polynomial	$d = 5$, $C = 2^3$	60.62	80.65	79.78	62.15	70.8
RBF	$C = 2^6$ $\gamma = 0.05$	73.61	77.55	84.83	66.05	75.51

The accuracy was determined by tenfold cross-validation approach. The training sample set D is splitted into ten subsets D_1, D_2, D_3 … D_{10}. One randomly chosen subset is test data and remaining subsets are training data set. This method was repeated ten times and average classification rate was computed across these ten trails as classification rate.

The optimal kernel parameters obtained in the above experimental procedure is then used in MC-SVM for classification.

Experiment 2: Linear SVM vs. polynomial SVM vs. RBF SVM

Table 5 presents classification rate for six subjects using the optimal kernel parameters determined in Experiment 1.

The average classification rate for 14 channel data is shown in Figure 9. SVM-Polynomial kernel provided better performance for Positive Valence/Low Arousal (PV/LA) quadrant and SVM-RBF provided better accuracy for the remaining three quadrants.

The best average classification rate of 73.61%, 84.83%, 66.05% was achieved using RBF for first, second and fourth quadrant, respectively. Polynomial SVM gives the best average rate of 80.65% for second quadrant. The low classification rate was achieved for classifying emotions in the first and fourth quadrant. The reason for the poor performance is due to the smaller number of training sets available for those emotions. As a result of this, the model created from EEG training samples could not generalise well on the EEG test sample. By increasing the number of training samples, a better model can be constructed that can overcome this problem.

Experiment 3: 14 channel EEG data vs. 9 channel EEG data

Tables 5 and 6 present classification rate for 14 channel and 9 channel EEG using MC-SVM with linear, polynomial (degree = 5) and RBF kernels ($C = 2^6$ & $\gamma = 0.05$), respectively.

From the results, we inferred that 14 channel EEG data performed better than 9 channel EEG data for all three types of classifier. The comparison result is shown in Figure 10.

Table 5 Classification rate for 14 channel EEG data using SVM with different kernels

	PV/HA			*PV/LA*			*NV/HA*			*NV/LA*		
	Eureka, Curious			*Confusion*			*Boredom*			*Angry, anxiety, fear, frustration*		
	14 channels											
	Linear	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*
Learner I	73.57	65.42	80.00	80.32	83.23	78.67	81.67	79.81	85.43	57.62	60.64	62.61
Learner Π	65.34	56.61	73.87	75.31	79.08	76.89	81.25	77.89	86.78	58.81	62.04	65.78
Learner III	71.42	67.82	79.76	78.89	80.04	76.32	80.76	80.76	85.32	55.93	6136	65.42
Learner IV	69.67	58.65	75.43	76.95	79.67	7735	81.03	8037	85.43	59.82	63.11	70.17
Learner V	59.07	5432	63.23	80.47	80.67	77.29	81.43	8037	82.71	55.62	64.89	66.89
Learner VI	67.43	60.89	69.34	78.46	81.23	78.76	81.85	79.45	83.32	56.73	60.85	65.43
Average	67.75	60.62	**73.61**	78.4	**80.65**	77.55	81.33	79.78	**84.83**	57.42	62.15	**66.05**

Table 6 Classification rate for 9 EEG channel data using SVM with different kernels of EEG *frequency-Time analysis*

	PV/HA			*FV/LA*			*NY/HA*			*NY/LA*		
	Eureka, Curious			*Confusion*			*Boredom*			*Angry, anxiety, fear, frustration*		
	nine channels											
	Linear	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*	*Linear*	*Polynomial*	*RBF*
Learner I	61.11	54.61	63.67	70.32	71.25	73.23	68.92	69.81	65.43	49.82	60.23	54.32
Learner Π	61.85	62.78	68.89	74.31	71.87	69.08	71.56	65.89	66.78	45.62	64.67	58.65
Learner III	60.24	52.42	67.32	72.89	69.76	70.04	70.26	67.76	65.32	46.73	57.21	65.42
Learner IV	62.67	60.17	61.35	72.14	66.43	79.67	69.41	6337	62.43	49.82	63.43	60.89
Learner V	59.57	59.89	70.29	70.67	67.23	70.67	67.32	6037	67.71	47.62	54.23	67.82
Learner VI	61.36	60.43	66.76	71.46	7034	71.65	71.02	59.45	69.32	48.81	61.11	56.61
Average	61.13	5838	**66.38**	71.97	69.48	**72.39**	**69.75**	64.44	66.17	48.07	60.14	**60.62**

Figure 9 Classification rate of linear, polynomial, RBF kernel function for four quadrants

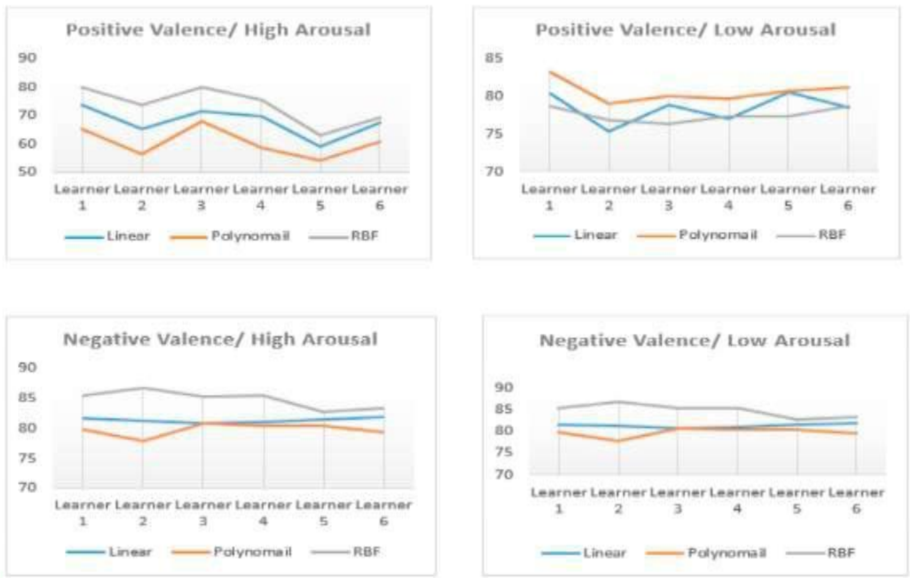
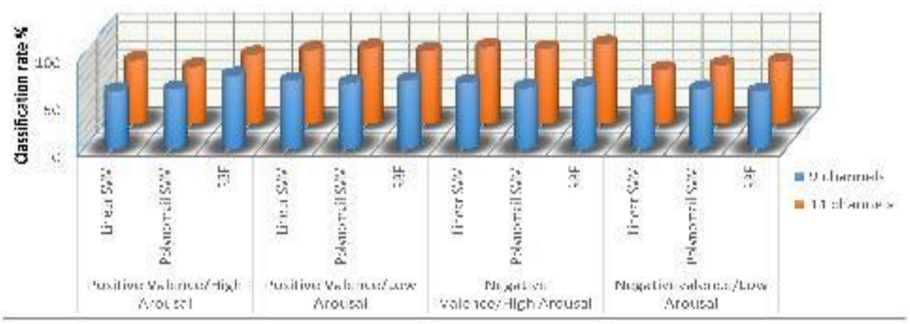


Figure 10 Comparison of classification rate for 14 channel and 9 channel EEG data



5.1 Comparison of our study with other studies

The accuracy of our system is compared with other studies and is shown in Table 7. For studies based on two-dimensional model, classification rate is calculated for two dimensions valence and arousal separately. Studies carried out for detecting emotions based on discrete model, average classification rate was computed based on classification rate obtained for each emotion.

It is evident from the table that our approach has yielded good accuracy compared with many approaches. Also, it recognised wider range of emotions and used less number of electrodes.

Table 7 Comparison of proposed work with other studies

Study	*Stimuli*	*Class*	*Feature extraction*	*Classifier*	*Results*	
					Arousal	*Valence*
			DEAP data set			
(Chung and Yoon, 2012)	Video	5	Not specified	Bayesian	66.6%	53.4%
(Liu and Sourina, 2013)	Video	4	Spectral + Fractal Dimension	SVM	65.32%	
(Zhang et al., 2013)	Video	–	–	Ontology	81.74%	75.19%
(Zheng et al., 2015)	Video	4	PSD, DE, DASM, RAS M, ASM, JDCAU	KNN, LFLSYM	69.67%	
			Own Data			
(Lin et al., 2010)	Audio	4	ST Fourier Transform	SVM	82.3%	
(Wang et al., 2011)	Video	4	FFT	KNN. MLP,SVM	65.51% (SVM)	
(Bajaj and Pachori, 2015)	Video & audio	4	WT	SVM	84.79%	
			DEAP + own data			
Our approach	E-learning content	8	HHT	MC-SVM with kernel function	73.61%, 80.65% (first & second quadrants)	84.83 % & 66.05% (third & fourth quadrants)

6 Conclusion

This work proposed a systematic approach and tested it for recognising emotion from EEG. Using this approach, we investigated various emotional states of a learner in e-learning environment. A set of e-learning contents were designed by subject experts to arouse eight emotions for learners and EEG data were collected while studying the materials through e-learning system. To assess the association between the brain activity and emotions, collected EEG data were analysed in time-frequency domain using HHT approach. A multiclass SVM is trained using DEAP data set and data obtained from our experiments. As the performance of the SVM depends on kernel function, we implemented three different kernel functions and investigated their performance. Experiments were conducted to determine the kernel function parameters C and γ so as to obtain best parameter setting for the classifier. The classification rate of SVM with three kernel functions with the obtained optimal kernel parameters were compared for four quadrants of valence- arousal model. The best average classification rate of 73.61%, 84.83%, 66.05% was achieved using SVM-RBF for first, third and fourth quadrant, respectively. Polynomial SVM gives the best average rate of 80.65% for second quadrant. Furthermore, another experiment was conducted to compare 14 channel and

9 channel EEG set-up. Experimental results demonstrated that 14 channel data set provided better classification accuracy. Our proposed approach yielded satisfactory results in recognising wider range of emotions with good accuracy.

6.1 Future scope

This research work is ongoing to locate optimal electrode placement settings by determining association between the areas of brain and emotions. Secondly, we want to address the issue of limited and unbalanced balanced data set causing under-fitting problems in the classifier. Thirdly, we would like to improve the accuracy of the proposed model by investigating multimodal approach and feature/decision fusion techniques.

References

Agrafioti, F., Hatzinakos, D. and Anderson, A.K. (2012) 'ECG pattern analysis for emotion detection', *IEEE Transactions on Affective Computing*, Vol. 3, No. 1, pp.102–115.

Atkinson, J. and Campos, D. (2016) 'Improving BCI-based emotion recognition by combining EEG feature selection and kernel classifiers', *Expert Systems with Applications*, Vol. 47, pp.35–41.

Bajaj, V. and Pachori, R.B. (2015) 'Detection of human emotions using features based on the multiwavelet transform of EEG signals', *Brain–Computer Interfaces*, Vol. 74, pp.215–240.

Bourel, F., Chibelushi, C.C. and Low, A.A. (2002) 'Robust facial expression recognition using a state-based model of spatially-localised facial dynamics', *Proceedings of Fifth IEEE International Conference on Automatic Face and Gesture Recognition*, IEEE Computer Society, Washington, DC, pp.106–111.

Chung, S.Y. and Yoon, H.J. (2012) 'Affective classification using Bayesian classifier and supervised learning', *2th International Conference on Control, Automation and Systems (ICCAS)*, IEEE, Jeju, South Korea, pp.1768–1771.

Cohen, I., Garg, A. and Huang, T.S. (2000) 'Emotion recognition from facial expressions using multilevel HMM', *Neural Information Processing Systems*, Denver, CO.

Damasio, A.R., Grabowski, T.J., Bechara, A., Damasio, H., Ponto, L.L., Parvizi, J. and Hichwa, R.D. (2000) 'Subcortical and cortical brain activity during the feeling of self-generated emotions', *Nature Neuroscience*, Vol. 3, No. 10, pp.1049–1056.

Guangzuo, C. (2010) 'A cognitive learning model in classroom interaction', *Second International Conference on Computational Intelligence and Natural Computing Proceedings (CINC)*, Vol. 2, pp.285–288.

Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C. and Liu, H.H. (1998) 'The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis', *Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences*, Vol. 454, No. 1971, pp.903–995.

Juan, L. and Shaoqin, G. (2006) 'The study of strategy of emotional education in e-learning', *Journal of China Educational Technology*, Vol. 1, pp.57–59.

Khosrowabadi, R., Quek, C., Ang, K.K. and Wahab, A. (2014) 'ERNN: a biologically inspired feedforward neural network to discriminate emotion from EEG signal', *IEEE Transactions on Neural Networks and Learning Systems*, Vol. 25, No. 3, pp.609–620.

Koelstra, S., Muhl, C., Soleymani, M., Lee, J.S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A. and Patras, I. (2012) 'DEAP: a database for emotion analysis: using physiological signals', *IEEE Transactions on Affective Computing*, Vol. 3, No. 1, pp.18–31.

Li, W. and Xu, H. (2014) 'Text-based emotion classification using emotion cause extraction', *Expert Systems with Applications*, Vol. 41, No. 4, pp.1742–1749.

Lin, Y.P., Wang, C.H., Jung, T.P., Wu, T.L., Jeng, S.K., Duann, J.R. and Chen, J.H. (2010) 'EEG-based emotion recognition in music listening', *IEEE Transactions on Biomedical Engineering*, Vol. 57, No. 7, pp.1798–1806.

Liu, Y. and Sourina, O. (2013) 'Real-time fractal-based valence level recognition from EEG', *Transactions on Computational Science XVIII*, Vol. 7848, pp.101–120.

Mayer, J.D. and Geher, G. (1996) 'Emotional intelligence and the identification of emotion', *Intelligence*, Vol. 22, No. 2, pp.89–113.

Mayer, J.D. and Salovey, P. (1993) 'The intelligence of emotional intelligence', *Intelligence*, Vol. 17, No. 4, pp.433–442.

Murugappan, M., Ramachandran, N. and Sazali, Y. (2010) 'Classification of human emotion from EEG using discrete wavelet transform', *Journal of Biomedical Science and Engineering*, Vol. 3, No. 4, pp.390–396.

Ng, K.C. (2001) 'Using e-mail to foster collaboration in distance education', *Open Learning*, Vol. 16, No. 2, pp.191–200.

Nie, D., Wang, X.W., Shi, L.C. and Lu, B.L. (2011) 'EEG-based emotion recognition during watching movies', *2011 5th International IEEE/EMBS Conference on Neural Engineering (NER)*, IEEE Press, Mexico, pp.667–670.

Noriko, H.A.R.A. and Kling, R. (2003) 'Student's Distress with a web-based distance education course: an ethnographic study of participants' experiences', *Turkish Online Journal of Distance Education*, Vol. 4, No. 2. Available online at: http://tojde.anadolu.edu.tr/tojde10/articles/hara.htm

Papez, J.W. (1937) 'A proposed mechanism of emotion', *Archives of Neurology & Psychiatry*, Vol. 38, No. 4, pp.725–743.

Parker, J., Duffy, J., Wood, L., Bond, B. and Hogan, M. (2005) 'Academic achievement and emotional intelligence: predicting the successful transition from high school to university', *Journal of the First-Year Experience & Students in Transition*, Vol. 17, No. 1, pp.67–78.

Petrantonakis, P.C. and Hadjileontiadis, L.J. (2010) 'Emotion recognition from EEG using higher order crossings', *IEEE Transactions on Information Technology in Biomedicine*, Vol. 14, No. 2, pp.186–197.

Picard, R.W., Vyzas, E. and Healey, J. (2001) 'Toward machine emotional intelligence: analysis of affective physiological state', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 23, No. 10, pp.1175–1191.

Rizon, M., Murugappan, M., Nagarajan, R. and Yaacob, S. (2008) 'Asymmetric ratio and FCM based salient channel selection for human emotion detection using EEG', *WSEAS Transactions on Signal Processing*, Vol. 4, No. 10, pp.596–603.

Schaller, D.T., Allison -Bunnell, S., Borun, M. and Chambers, M.B. (2002) 'How do you like to learn? Comparing user preferences and visit length of educational web sites', *Various Studies*, Vol. 5, No. 2, pp.5–10.

Schuller, B., Reiter, S., Muller, R., Al-Hames, M., Lang, M. and Rigoll, G. (2005) 'Speaker independent speech emotion recognition by ensemble classification, *2005 IEEE International Conference on Multimedia and Expo*, 6–9 July, IEEE, Amsterdam, pp.864–867.

Sebe, N., Lew, M.S., Sun, Y., Cohen, I., Gevers, T. and Huang, T.S. (2007) 'Authentic facial expression analysis', *Image and Vision Computing*, Vol. 25, No. 12, pp.1856–1863.

Walker, M.E.B. (2006) *Emotional Intelligence and Academic Success in College*, Unpublished Doctoral Dissertation, The University of Southern Mississippi, Mississippi.

Wang, K., An, N., Li, B.N., Zhang, Y. and Li, L. (2015) 'Speech emotion recognition using Fourier parameters', *IEEE Transactions on Affective Computing*, Vol. 6, No. 1, pp.69–75.

Wang, X.W., Nie, D. and Lu, B.L. (2011) 'EEG-based emotion recognition using frequency domain features and support vector machines', *International Conference on Neural Information Processing*, Vol. 7062, pp.734–743.

Wegerif, R. (1998) 'The social dimension of asynchronous learning networks', *Journal of Asynchronous Learning Networks*, Vol. 2, No. 1, pp.34–49.

Yin, G.M. and Guo, G.X. (2010) 'An affective recognition-based architecture for intelligent learning environments', 2010 *International Conference on Computer Application and System Modeling (ICCASM 2010)*, Vol. 5, pp.V5-237–V5-239.

Zeng, Z., Pantic, M., Roisman, G.I. and Huang, T.S. (2009) 'A survey of affect recognition methods: audio, visual, and spontaneous expressions', *IEEE Transactions on Pattern Analysis and Machine Intelligence*, Vol. 31, No. 1, pp.39–58.

Zhang, X., Hu, B., Chen, J. and Moore, P. (2013) 'Ontology-based context modeling for emotion recognition in an intelligent web', *World Wide Web*, Vol. 16, No. 4, pp.497–513.

Zheng, W.L. and Lu, B.L. (2015) 'Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks', *IEEE Transactions on Autonomous Mental Development*, Vol. 7, No. 3, pp.162–175.

Zheng, W.L., Zhang, Y.Q., Zhu, J.Y. and Lu, B.L. (2015) 'Transfer components between subjects for EEG-based emotion recognition', *International Conference on Affective Computing and Intelligent Interaction (ACII)*, pp.917–922, doi:ITE10.1109/ACII.2015.7344684.