Real-time Subject-dependent EEG-based Emotion Recognition Algorithm

Yisi Liu and Olga Sourina

Fraunhofer IDM@NTU, Nanyang Technological University
Singapore
{LIUYS,EOSourina}@ntu.edu.sg

Abstract. In this paper, we proposed a real-time subject-dependent EEG-based emotion recognition algorithm and tested it on experiments' databases and the benchmark database DEAP. The algorithm consists of two parts: feature extraction and data classification with Support Vector Machine (SVM). Use of a Fractal Dimension feature in combination with statistical and Higher Order Crossings (HOC) features gave results with the best accuracy and with adequate computational time. The features were calculated from EEG using a sliding window. The proposed algorithm can recognize up to 8 emotions such as happy, surprised, satisfied, protected, angry, frightened, unconcerned, and sad using 4 electrodes in real time. Two experiments with audio and visual stimuli were implemented, and the Emotiv EPOC device was used to collect EEG data.

Keywords: emotion recognition, EEG, emotion recognition algorithms, Emotiv EPOC, Valence-Arousal-Dominance model

1 Introduction

Recently, the EEG devices became wireless, more portable, wearable and easy to use, thus more research can be done on real-time emotion recognition algorithms. Emotion recognition algorithms can be subject-dependent and subject-independent. Subject-dependent algorithms have a better accuracy than subject-independent algorithms but the system training session for each individual user should be designed and implemented in the subject-dependent algorithms.

In this paper, we proposed and implemented a real-time subject-dependent algorithm based on the Valence-Arousal-Dominance (VAD) emotion model. A combination of features including Fractal Dimension (FD) was used because FD values reflect nonlinearity of EEG signals. Fractal Dimension analysis is a suitable approach for analyzing nonlinear systems and can be used in real-time EEG signal processing [4, 72]. Early works show that Fractal Dimension can reflect changes in EEG signals [58], and Fractal Dimension is varied for different mental tasks [48]. In [63, 66], music was used as a stimulus to elicit emotions, and Fractal Dimension was applied for the analysis of the EEG signal. In [5], it was demonstrated that the difference between positive and negative emotions can be discovered by estimating the dimensional complexity of the signal. Recent supporting evidence such as [23] and [24] shows that Fractal Dimension can reflect the activity of the sensorimotor cortex. More supporting evidence to successful use of Fractal Dimension in EEG analysis in different applications is described in [48, 58, 63, 66]. These works show that Fractal Dimension based EEG analysis is a potentially promising approach in EEG-based emotion recognition.

Our hypothesis is that the feeling of changes can be noticed from EEG as fractal dimension changes. In 2008, we started to use fractal dimension to recognize positive and negative emotions from EEG [63]. In 2010, we proposed to use Higuchi algorithm for fractal feature extraction for real-time emotion recognition. We calculated subject dependent thresholds of emotions recognition, and we visualized emotions in real time on a virtual avatar [43, 44]. At the same year, [33] and [26] also confirmed that Higuchi fractal dimension can be used in EEG-based emotion recognition algorithms. In 2011, we studied the fractal dimension methods such as box-counting and Higuchi using mono fractal signals generated by Brownian and Weierstrass functions [73] and in [64] both algorithms were applied to recognize high/low arousal and positive/negative valence [64]. In [46], two affective EEG databases were presented; two experiments were conducted to set up the databases. Audio and visual stimuli were used to evoke emotions during the experiments. In [46] and this work, we proposed to use a FD feature to improve emotion recognition algorithm accuracy. The algorithm consists of two parts: feature extraction and classification with the Support Vector Machine (SVM) classifier. Use of a Fractal Dimension feature in combination with statistical and Higher Order Crossings (HOC) features gave the results with the best accuracy and with adequate computational time. The features' values were calculated from EEG using a sliding window.

In the VAD model, the emotions are described as follows: a "satisfied" emotion is defined as a positive/ low arousal/ high dominance emotion, a "happy" emotion is defined as a positive/ high arousal/ high dominance emotion, a "surprised" emotion is defined as a positive/ high arousal/ low dominance emotion, a "protected" emotion is defined as a positive/ low arousal/ low dominance emotion, a "sad" emotion is defined as a negative/ low arousal/ low dominance emotion, a "unconcerned" emotion is defined as a negative/ low arousal/ high dominance emotion, a "angry" emotion is defined as a negative/ high arousal/ high dominance emotion and a "frightened" emotion is defined as a negative/high arousal/low dominance emotion [51], etc. The proposed algorithm should be tested on the EEG databases labeled with emotions where emotions were induced by visual, audio, and combined (music video) stimuli, and the best combination of features should be proposed. In this paper, 2 series of experiments on emotion induction with audio stimuli and with visual stimuli were designed and implemented based on the Valence-Arousal-Dominance emotion model. The sounds were chosen to induce happy, surprised, satisfied, protected, angry, frightened, unconcerned, and sad emotions from International Affective Digitized Sounds (IADS) [13], and the visual stimuli were chosen from International Affective Picture System (IAPS) database [41]. The data were collected from 14 subjects in Experiment 1 and 16 subjects in Experiment 2. The questionnaire and Self-Assessment Manikin (SAM) [12] technique were applied. Two databases with EEG data labeled with 8 emotions were created. Recently, the DEAP benchmark database that used music video stimuli for emotion induction became available [35]. The proposed algorithm was tested on the benchmark DEAP database and on our own two experiments' databases.

The paper is organized as follows. In Section 2, emotion classification models, and EEG-based emotion recognition algorithms are reviewed. Mathematical models of the channel choice algorithm, statistical features, Higher Order Crossings (HOC), Fractal Dimension (FD) algorithm and the Support Vector Machine classifier that were used for feature extraction and classification are introduced in Section 3. In Section 4, the proposed and implemented experiments are given. The affective EEG database DEAP is also briefly described. A real-time subject-dependent algorithm is described in Section 5. The algorithm results and discussion are given in Section 6. Finally, Section 7 concludes the paper.

2 Background

2.1 Emotion Classification Models

The most widely used approach to represent emotion is the bipolar model with valence and arousal dimensions proposed by Russell [60]. In this model, valence dimension ranges from "negative" to "positive", and arousal dimension ranges from "not aroused" to "excited". The 2-Dimensional (2D) model can locate the discrete emotion labels in its space [50], and it could define emotions which are even without discrete emotion labels. However, emotion of fear and anger cannot be differed if they were defined by the 2D model as they both have the same high arousal and negative valence level values.

In order to get a comprehensive description of emotions, Mehrabian and Russell proposed 3-Dimensional (3D) Pleasure (Valence)-Arousal-Dominance (PAD) model in [51] and [52]. "Pleasure-displeasure" dimension of the model equals to the valence dimension mentioned above, evaluating the pleasure level of the emotion. "Arousal-non-arousal" dimension is equivalent to the arousal dimension, referring to the alertness of an emotion. "Dominance-submissiveness" dimension is a newly extended dimension, which is also named as a control dimension of emotion [51, 52]. It ranges from a feeling of being in control during an emotional experience to a feeling of being controlled by the emotion [10]. It makes the dimensional model more complete. With the Dominance dimension, more emotion labels can be located in the 3D space. For example, happiness and surprise are both emotions with positive valence and high arousal, and it can be differentiated by their dominance level since happiness is with high dominance, whereas surprise is with low dominance [51].

In our work, we use the 3-dimensional emotion classification model.

2.2 EEG-based Emotion Recognition Algorithms

The EEG-based emotion recognition algorithms are different on their dependence on subjects during the recognition and they can be implemented in either a subject-dependent or a subject-independent way. The advantage of subject-dependent recognition is that a higher accuracy can be achieved since the classification is catered for each individual, but the disadvantage is that every time a classifier is needed to be trained for a new subject.

[15, 29, 42, 43, 61, 74] are examples of subject-dependent algorithms. In [42, 43] and [61], the discrete emotion model was used. Four emotions such as joy, anger, sadness, and pleasure were recognized in [42] with 32 channels and an averaged accuracy of 82.29% using the differential asymmetry of hemispheric EEG power spectra and SVM as a classifier. In [43], 6 emotions such as pleasure, satisfaction, happiness, sadness, frustration, and fear were recognized with the proposed subject-dependent algorithm. Three emotional reactions including "pleasant", "neutral" and "unpleasant" were recognized in [61] with 4 channels, and the average accuracy is 66.7%. In [15, 29, 74], the dimensional emotion model was used. Positive and negative emotional states based on the valence dimension in the 2D emotional model were recognized in [74], and the accuracy obtained was 73% using 3 channels. [15] recognized positive and negative states with 4 channels and obtained an accuracy of 57.04%. [29] recognized positive/ negative valence states with the best mean accuracy of 83.1%, and strong/calm arousal states with the best mean accuracy of 66.51% using 32 channels.

[8, 16, 62, 70] are examples of subject-independent algorithms. [16, 62, 70] employed the discrete emotion model. By using the powers of different frequency bands of EEG signals as features, [16] got maximum 56% accuracy for 3 emotional states such as boredom, engagement, and anxiety detection. By using the statistical features and SVM, five emotions such as joy, anger, sadness, fear and relaxation were recognized with accuracy 41.7% in [70]. Although [8] can achieve an average accuracy of 94.27% across five emotions, 256 channels were compulsory in the recognition. [62] used the dimensional emotion model, and it obtained accuracies of 62.1% and 50.5% for detecting 3 levels of arousal and valence respectively, and 32 channels were needed in the algorithm.

In [56], both subject-dependent and subject-independent algorithms were proposed. 4 channels were used in the recognition. In the subject-dependent case of [56], the accuracy ranges from 70% to 100%, and in the subject-independent case, the accuracy drops by 10% to 20%. It is important to notice that in the reviewed works, the reported accuracy was calculated on their own datasets.

All the above-mentioned works show that the accuracy of the subject-dependent algorithms is generally higher than subject-independent algorithms. Thus, we developed a subject-dependent algorithm in our work. The number of emotions that is possible to recognize and the number of the electrodes that is used are very important for the algorithms comparison. For example, although the accuracy that was obtained in [42] is higher than in [74], 32 channels were needed in [42] compared with 3 channels used in [74]. Besides that, if the algorithm is developed for real-time applications, the time needed for features extraction and the number of channels used should be minimized. If more electrodes are used, the comfort level of the user who wears the device decreases as well. Thus, our main objective is to propose an algorithm performing with adequate accuracy in real-time applications.

3 Method

3.1 The Fisher Discriminant Ratio

The Fisher Discriminant Ratio (FDR) is a classical approach that is used to select channels [7, 19, 40]. The output of FDR is a score corresponding to each channel. The selection of channels will follow the rank of their FDR scores. The formula of FDR value calculation is as follows:

$$FDR(p) = \frac{\sum_{i=1}^{C}\sum_{j=1}^{C}(\mu_p^i - \mu_p^j)^2}{\sum_{i=1}^{C}(\sigma_p^i)^2}. \tag{1}$$

where C is the number of classes, p is the channel index, μ_p^i is the mean value of the feature from the pth channel for the ith class, and σ_p^i is the standard deviation of the feature from the pth channel for the ith class [34].

3.2 Statistical, Higher Order Crossings and Fractal Dimension Feature Extraction

Although the EEG signal is nonlinear [38, 39], little has been done to investigate its nonlinear nature when emotion recognition research is conducted. Linear analysis such as Fourier Transform only preserves the power spectrum in the signal, but destroys the spike-wave structure [67].

In this work, we proposed to use Fractal Dimension feature in combination with statistical features [57], Higher Order Crossings (HOC) [32, 55] to improve emotion recognition accuracy. Statistical and HOC features were used as they gave the highest emotion recognition accuracy as it was described in [55, 57, 70]. In this work, the Higuchi algorithm [25] was proposed to be used for FD values calculation. The algorithm gave better accuracy than other FD algorithms as it was shown in [73]. Details of these algorithms are given as below.

Statistical Features

1. The means of the raw signals

$$\mu_X = \frac{1}{N}\sum_{\mathrm{n}=1}^{N} X(n). \tag{2}$$

2. The standard deviations of the raw signals

$$\sigma_X = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(X(n)-\mu_X)^2}. \tag{3}$$

3. The means of the absolute values of the first differences of the raw signals

$$\delta_X = \frac{1}{N-1}\sum_{n=1}^{N-1}\left|X(n+1)-X(n)\right|. \tag{4}$$

4. The means of the absolute values of the first differences of the normalized signals

$$\overline{\delta_X} = \frac{1}{N-1}\sum_{n=1}^{N-1}\left|\overline{X}(n+1)-\overline{X}(n)\right| = \frac{\delta_X}{\sigma_X}. \tag{5}$$

5. The means of the absolute values of the second differences of the raw signals

$$\gamma_X = \frac{1}{N-2}\sum_{n=1}^{N-2}\left|X(n+2)-X(n)\right|. \tag{6}$$

6. The means of the absolute values of the second differences of the normalized signals

$$\overline{\gamma_X} = \frac{1}{N-2}\sum_{n=1}^{N-2}\left|\overline{X}(n+2)-\overline{X}(n)\right| = \frac{\gamma_X}{\sigma_X}. \tag{7}$$

Thus, the feature vector composed is

$$\boldsymbol{FV_{Statistical}} = [\mu_X, \sigma_X, \delta_X, \overline{\delta_X}, \gamma_X, \overline{\gamma_X}]. \tag{8}$$

HOC-Based Features The algorithm of HOC is given as follows.

The input data is a finite zero-mean series $\{X_n\}$,$n = 1, ..., N$.

First, a sequence of filters are applied on the input data

$$\nabla^{k-1}X_n \equiv \sum_{j=1}^{k}\frac{(k-1)!}{(j-1)!(k-j)!}(-1)^{(j-1)}X_{n-j+1}. \tag{9}$$

where ∇^{k-1} denotes a sequence of filters, when $k = 1$, it becomes the identity filter.

Then the number of zero-crossings associated with a particular filter is counted. To get the counts of zero-crossings,

$$Z_n(K) = \begin{cases} 1 & if \nabla^{k-1}X_n \geq 0 \\ 0 & if \nabla^{k-1}X_n < 0 \end{cases} \tag{10}$$

is used and

$$D_k = \sum_{n=2}^{N} [Z_n(k) - Z_{n-1}(k)]^2. \tag{11}$$

represents the number of zero crossings.

As a result, the feature vector [55] is constructed as

$$\boldsymbol{FV_{HOC}} = [D_1, D_2, ..., D_k]. \tag{12}$$

Higuchi Algorithm Let $X(1), X(2), \ldots, X(N)$ be a finite set of time series samples. Then, the newly constructed time series is

$$X_t^m : X(m), X(m+t), \ldots, X\left(m + \left[\frac{N-m}{t}\right] \cdot t\right). \tag{13}$$

where $m = 1, 2, ..., t$ is the initial time and t is the interval time [25].

For example, if $t = 3$ and $N = 100$, the newly constructed time series are:
$X_3^1 : X(1), X(4), ..., X(100)$,$X_3^2 : X(2), X(5), ..., X(98)$,
$X_3^3 : X(3), X(6), ..., X(99)$.

t sets of $L_m(t)$ are calculated by

$$L_m(t) = \frac{\left\{\left(\sum_{i=1}^{\left[\frac{N-m}{t}\right]} |X(m+it) - X(m+(i-1)\cdot t)|\right) \frac{N-1}{\left[\frac{N-m}{t}\right]\cdot t}\right\}}{t}. \tag{14}$$

$\langle L(t)\rangle$ denotes the average value of $L_m(t)$, and one relationship exists

$$\langle L(t)\rangle \propto t^{-dim_H}. \tag{15}$$

Then, the fractal dimension dim_H could be obtained by logarithmic plotting between different t(ranging from 1 to t_{max}) and its associated $\langle L(t)\rangle$ [25].

$$dim_H = \frac{\ln \langle L(t)\rangle}{-\ln t}. \tag{16}$$

Thus, the feature vector composed is

$$\boldsymbol{FV_{FD(Higuchi)}} = [dim_H]. \tag{17}$$

3.3 Support Vector Machine Classifier

The goal of SVM method is to find a hyperplane of high dimensional space which can be used for classification [18]. SVM is a powerful classifier. It projects low dimension features into higher dimension using kernel functions which can solve the inseparable cases [53]. There are different types of kernel functions used in implemented classifiers. The polynomial kernel used in our work is defined as follows [17]:

$$K(x \cdot z) = (gamma \cdot x^T \cdot z + coef)^d. \tag{18}$$

where $x, z \in R^n$, $gamma$, and $coef$ are the kernel parameters, d denotes the order of the polynomial kernel and T is the transpose operation. More information on SVM classifiers can be found in [18].

4 Experiment

We designed and carried out two experiments with audio and visual external stimuli to collect EEG data based on the Valence-Arousal-Dominance emotion model. The obtained EEG data with different emotional labels were used to test the proposed algorithm.

4.1 Stimuli

In Experiment 1, sound clips selected from the International Affective Digitized Sounds (IADS) database [13] that follows the Valence-Arousal-Dominance emotion model were used to induce emotions. The choice of sound clips is based on their Valence, Arousal and Dominance level rating in the IADS database. The experiment is composed of 8 sessions, and 5 clips targeting one emotion were played in each session. The details of stimuli used to target emotions in each session are given in Table 1.

In Experiment 2, we elicited emotions with visual stimuli selected from International Affective Picture System (IAPS) database [41].The experiment was also composed of 8 sessions, and 4 pictures targeting one emotion were shown in each session. The details of stimuli targeting emotions in each session are given in Table 2.

Table 1: Stimuli used in Experiment 1.

Session No.	Targeted States	Stimuli No.
Session1	Positive/ Low arousal/ Low dominance (PLL)	170, 262, 368, 602, 698
Session2	Positive/ Low arousal/ High dominance(PLH)	171, 172, 377, 809, 812
Session3	Positive/ High arousal/ Low dominance (PHL)	114, 152, 360, 410, 425
Session4	Positive/ High arousal/ High dominance (PHH)	367, 716, 717, 815, 817
Session5	Negative/ Low arousal/ Low dominance (NLL)	250, 252, 627, 702, 723
Session6	Negative/ Low arousal/ High dominance (NLH)	246, 358, 700, 720, 728
Session7	Negative/ High arousal/ Low dominance (NHL)	277, 279, 285, 286, 424
Session8	Negative/ High arousal/ High dominance (NHH)	116, 243, 280, 380, 423

Table 2: Stimuli used in Experiment 2.

Session No.	Targeted States	Stimuli No.
Session1	Positive/ Low arousal/ Low dominance (PLL)	7632, 5890, 5982, 7497
Session2	Positive/ Low arousal/ High dominance(PLH)	5000, 1604, 2370, 5760
Session3	Positive/ High arousal/ Low dominance (PHL)	5260, 1650, 8400, 849
Session4	Positive/ High arousal/ High dominance (PHH)	5626, 8034, 8501, 8200
Session5	Negative/ Low arousal/ Low dominance (NLL)	2682, 2753, 9010, 9220
Session6	Negative/ Low arousal/ High dominance (NLH)	2280, 7224, 2810, 9832
Session7	Negative/ High arousal/ Low dominance (NHL)	6230, 6350, 9410, 9940
Session8	Negative/ High arousal/ High dominance (NHH)	2458, 3550.2, 2130, 7360

4.2 Subjects

In Experiment 1, there are a total of 14 (9 females and 5 males) subjects participating in the experiment. In Experiment 2, there are a total of 16 (9 females and 7 males) subjects participating in the experiment. All of them are university students and staff whose age ranged around 20 to 35 years old and without auditory deficit or any history of mental illness.

4.3 Procedure

After a participant was invited to a project room, the experiment protocol and the usage of a self-assessment questionnaire were explained to him/her. The subjects needed to complete the questionnaire after the exposure to the audio/visual stimuli. The Self-Assessment Manikin (SAM) technique [12] was employed which used the 3D model with valence, arousal and dominance dimensions and nine levels indicating the intensity in all dimensions. In the questionnaire, the subjects were also asked to describe their feelings in any words including the emotions like happy, surprised, satisfied, protected, angry, frightened, unconcerned, sad or any other emotions they feel. The experiments were done with one subject at each time. The audio experiment was conducted following the standard procedure for emotion induction with audio stimuli [22, 42]. Therefore, in Experiment 1, the participants were asked to close their eyes to avoid artifacts and to be focused on hearing. In Experiment 2, the subjects were asked to avoid making movement except working on the keyboard.

The design of each session in Experiment 1 is as follows.

1. A silent period is given to the participant to calm down (12 seconds).
2. The subject is exposed to the sound stimuli (5clips x 6 seconds/clip=30 seconds).
3. The subject completes the self-assessment questionnaire.

In summary, each session lasted 42 seconds plus the self-assessment time.

The construction of each session in Experiment 2 is as follows.

1. A black screen is shown to the participant (3 seconds).

2. A white cross in the center of the screen is given to inform the subject that visual stimuli will be shown (4 seconds).
3. The subject is exposed to the pictures (4 pictures x 10 seconds/clip=40 seconds).
4. The black screen is shown to the participant again (3 seconds).
5. The subject completes the self-assessment questionnaire.

In summary, each session lasted 50 seconds plus the self-assessment time.

4.4 EEG recording

In this work, we used Emotiv [2] device with 14 electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 and these locations are standardized by the American Electroencephalographic Society [3] (plus CMS/DRL as references) for both Experiment 1 and 2. The technical parameters of the device are given as follows: bandwidth - 0.2-45Hz, digital notch filters at 50Hz and 60Hz; A/D converter with 16 bits resolution and sampling rate of 128Hz. The data are transferred via a wireless receiver. Recently, Emotiv devices have become popular for research [54, 59]. The reliability and validity of the EEG data collected by Emotiv device was done in [21, 68]. EEG data recorded from standard EEG device and Emotiv were compared, and the results showed that the Emotiv device could be used as the standard EEG device in real-time applications where fewer electrodes were needed [68] and it is creditable to be used in applications such as games [21].

4.5 Analysis of Self-Assessment Questionnaire

Even though the stimuli were selected with targeted emotional states, we found out from the self-report questionnaire records that some emotions were not confirmed by the subjects. Our analysis was based on the questionnaire which gave us the recorded participants' feelings. We did not consider the data from the cases when the targeted emotion was not induced according to the self-assessment questionnaire record.

Since the aim of this work is to develop an algorithm to detect up to 8 emotions defined by combinations of high/low arousal levels, positive/negative valence levels, and high/low dominance levels, and in the benchmark DEAP database (described in Section 4.6) and two experiments' databases the self-assessment questionnaire has 9 levels rating in each emotional dimension, the level 5 was used as the thresholds to identify high and low values at each dimensional level as shown in Table 3. Here, 5 is considered as an intermediate level which does not belong to neither a high nor a low state, thus the data with rating 5 were not used in the following processing. For example, if the targeted emotion is Positive/Low arousal/Low dominance, then the subject's data will be considered compatible with the targeted emotion if the subject's rating for valence dimension is larger than 5, the rating for arousal dimension is lower than 5, and the rating for dominance level is lower than 5.

Table 3: The conditions of different states in the analysis of self-assessment questionnaire.

Emotional Dimension	Targeted States	Conditions
Valence Dimension	Positive	Valence rating>5
	Negative	Valence rating<5
Arousal Dimension	High	Arousal rating>5
	Low	Arousal rating<5
Dominance Dimension	High	Dominance rating>5
	Low	Dominance rating<5

4.6 Affective EEG database DEAP

Since EEG-based emotion analysis is attracting more and more attention, the DEAP database labeled with emotions was established and published [35]. It has a relatively large amount of subjects (32 subjects) who participated in the data collection. The stimuli to elicit emotions used in the experiment are 40 one-minute long music videos. In the DEAP database, a Biosemi ActiveTwo device with 32 EEG channels [1] was used for the data recording, which could give a more comprehensive understanding of brain activity.

There are a number of datasets available in the DEAP database. Here, we used the dataset after preprocessing [36]. The sampling rate of the original recorded data is 512 Hz, and the set of preprocessed data are down sampled to 128 Hz. The artifacts such as EOG were removed from the DEAP EEG data during the preprocessing. As suggested by the developers of DEAP, this dataset is well-suited to those who want to test their own algorithms. Thus, in our work, we used this dataset to validate the algorithm. More details about the DEAP database can be found in [35] and [36].

5 Implementation

5.1 Fractal Features

In this work, the FD values were proposed to be used as features to improve the accuracy of emotion recognition from EEG signals. To calculate one FD value per finite set of time series samples, the Higuchi algorithm described in Section 3.2 was implemented and validated on the standard mono fractal signal generated by the Weierstrass function where the theoretical FD values were known in advance [49]. The size of the finite set N defines the size of the window in our emotion recognition algorithm. Fig. 1 shows the result of the calculation of FD values of the signals generated by the Weierstrass function with different window sizes. As it is seen from the graph, the FD values calculated with the window size equal to 512 samples are more close to the theoretical values. Thus, in our algorithm, the size of the window of 512 samples was chosen. For each window size N, we used different t_{max} values ranging from 8 to 64 in (15)-(16) to compute the FD values. With $N = 512$, the value of t_{max} was set to 32 since it has the lowest error rate as shown in Fig. 2.

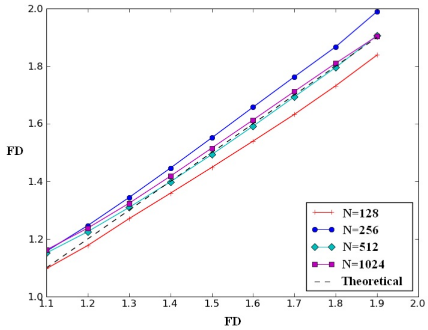

Fig. 1: FD values of the signals generated by the Weierstrass function calculated by the Higuchi algorithm with different window sizes.

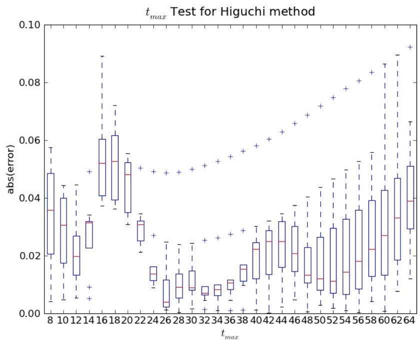

Fig. 2: Abs(error) for different t_{max} with $N = 512$.

5.2 Channel Choice

The classical FDR method [34] was applied for the channel selection [7, 19, 40]. A non-overlapping sliding window with size of 512 samples was used for FD feature calculation. Channel ranking for 32 subjects from the DEAP database was calculated. In DEAP databases, there are 40 experimental trials labelled with arousal, valence and dominance ratings, and in our case (recognition of 8 emotions), for every subject, one trial was selected per emotion. As a result, up to

8 trials EEG data were selected with the corresponding emotions such as PLL, PLH, PHL, PHH, NLL, NLH, NHL, and NHH in the following processing. If the subject has more than one trial that labeled with the same emotions, the trial with extreme rating will be selected. For example, for the state of Arousal>5, Valence>5, Dominance>5, a trial with arousal rating 9, valence rating 8, dominance rating 8 will be used instead of a trial with arousal rating 6, valence rating 6, dominance rating 7. EEG data collected during playing the first 53 seconds of the video were used to calculate FD values in each session. The mean FDR scores for each channel were computed across all the 32 subjects. By using the data provided by the DEAP database, we can have more subjects to get a more general channel rank patterns. The final channel rank is FC5, F4, F7, AF3, CP6, T7, C3, FC6, P4, Fp2, F8, P3, CP5, O1, F3, P8, CP2, CP1, P7, Fp1, PO4, O2, Pz, Oz, T8, FC2, Fz, AF4, PO3, Cz, C4, FC1. The ranking of each channel is visualized in Fig. 3 using EEGLAB [20]. The visualization is based on the mean FDR scores across different subjects for each channel. It is a standard approach to use the channel rank to show spatial pattern. For example, [7] visualizes the weights of the spatial filters obtained from the sparse common spatial pattern (SCSP) algorithm. [40] uses the channel rank score to show the activated brain regions during the motor imagination tasks. The values were scaled for better visualization. From the figure, it can be seen that the frontal lobe is the most active because the most discriminant channels belong to the frontal lobe. Previous research has confirmed that the orbitofrontal cortex, anterior cingulated cortex, amygdala, and insula are highly involved in emotion processing [69]. For example, it shows that negative emotions increase the amygdale activation [14]. However, the subcortical structures such as amygdala cannot be detected directly by EEG signals which are recorded from the scalp. The amygdale connects and interacts with frontal cortex and emotions are experienced as a result [11, 31]. The visualization in Fig. 3 complies with the above-mentioned findings about the importance of frontal lobe in the emotion processing. Then, we followed the final channel rank to calculate the classification accuracy and to choose the number of the channels for our algorithm. The Support Vector Machine classifier described in Section 3.3, implemented by LIBSVM [17] with polynomial kernel for multiclass classification was used to compute the accuracy of emotion recognition using a different number of channels following the rank. 5-fold cross validation of the data was applied: first, the raw data were partitioned into 5 sets without overlapping, and then features were extracted from each set. During the classification phase, 4 sets were used as training sets, and 1 set was used as validation data for testing. The process was run 5 times, and every set was used as the testing data for once. The mean accuracy of the classification in 5 runs was computed as the final estimation of the classification accuracy. The cross-validation can allow us to avoid the problem of over fitting [28]. The parameters of the SVM classifier were set according to [55] where high accuracy of emotion classification was achieved with different feature types as follows: the value of $gamma$ in (18) was set to 1, $coef$ was set to 1 and order d was set to 5. A grid-search approach was also applied to select the SVM ker-

nel parameters, and the classification accuracy of emotion recognition showed that the above-mentioned parameters were the optimal choice. Fig. 4 shows the mean accuracy of emotion classification over the number of the best channels following the obtained channel rank for subjects who have EEG data labeled with 8, 7, 6 and 5 emotions. Here, FD features were used in the classification, and they were calculated by using a sliding window with size of 512 and moving by 128 new samples (the overlapping rate was 384/512) each time. As it is shown in Fig. 4, in order to minimize the number of channels used, based on the accuracy, the top 4 channels are considered as the optimum choice that can be used for emotion recognition with an adequate accuracy. These 4 channels including FC5, F4, F7, and AF3 electrode positions correspond to the frontal lobe location (Fig. 5). It complies with research results described in [9, 30, 37, 71] where correlation between emotions and the signal activities in the frontal lobe was studied, and the close relationship is confirmed. The frontal lobe is believed to execute processes that require intelligence such as determination and assessment. Human emotions are also associated with the frontal lobe. [9] finds that the damage in prefrontal cortex may cause a weakened or even disabled generation of certain emotions; [37] shows that the prefrontal lobe area plays a role in linking reward to subject's pleasantness; [30] confirms that there is a lateralization pattern in the frontal lobe when processing positive and negative emotions; [71] discovers an asymmetrical pattern in the frontal lobe during the observation of pleasant/unpleasant advertisements.

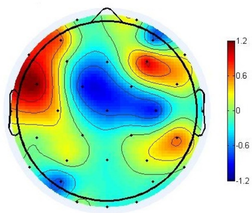

Fig. 3: Visualization of the ranking of 32 channels on the scalp.

5.3 Feature Extraction and Classification

We present a subject-dependent algorithm of human emotion recognition from EEG based on the Valence-Arousal- Dominance emotion model. The algorithm consists of two parts: features extraction with a sliding window and data classification with Support Vector Machine (SVM) in order to accomplish efficient emotion recognition. In our work, a 2-42 Hz bandpass filter was applied to the data since it could remove artifacts such as muscle contraction and control [6, 33]. We extract features from the entire EEG band from 2-42Hz instead of decomposing it to different frequency bands such as Alpha or Beta waves as it was done in [70] and [74]. As it was shown in Section 5.2, the FC5, F4, F7, and AF3 channels were chosen for the algorithm implementation. The feature vector $\boldsymbol{FV}$ for emotion classification is defined as follows:

$$\boldsymbol{FV} = [\boldsymbol{FV_1}, \boldsymbol{FV_2}, \boldsymbol{FV_3}, \boldsymbol{FV_4}]. \tag{19}$$

where 1 denotes FC5 channel, 2 denotes F4 channel, 3 denotes F7 channel, 4 denotes AF3 channel, and $\boldsymbol{FV_i}$ is the feature vector per channel. Here, the $\boldsymbol{FV_i}$ is composed by the statistical features given in (8), HOC features given in (12), FD features given in (17) or the combinations of different features $\boldsymbol{FV_{combination_1}}$ and $\boldsymbol{FV_{combination_2}}$ as given below in (20) and (21). Normalization is applied to the FD, statistical features and HOC features across the four channels in (19).

$$\boldsymbol{FV_{combination_1}} = [\mu_X, \sigma_X, \delta_X, \overline{\delta_X}, \gamma_X, \overline{\gamma_X}, dim_H]. \tag{20}$$

$$\boldsymbol{FV_{combination_2}} = [D_1, D_2, ..., D_k, \mu_X, \sigma_X, \delta_X, \overline{\delta_X}, \gamma_X, \overline{\gamma_X}, dim_H]. \tag{21}$$

Here, $\boldsymbol{FV_{combination_1}}$ employs 6 statistical and 1 FD features, $FV_{combination_2}$ employs HOC features, 6 statistical and 1 FD features. In (20) and (21), normalization is applied to the statistical features, HOC features, and FD features across the four channels before combining the features. As it was determined in Section 5.1 and 5.2, to obtain training and testing samples for the SVM classifier, a sliding window with the size of 512 with 384 samples overlapping was used to calculate the statistical features (as in (8)), HOC features (as in (12)), and the combined features (as in (20) and (21)). In the DEAP database, the EEG data collected from 60 seconds when the videos were played were used. As in Experiment 1 only 5 clips were selected in each session, EEG data collected from the first 30 seconds when the sound clips were exposed to the subjects were used. In Experiment 2, EEG data collected from the first 30 seconds when the pictures were shown to the subjects were used. Different HOC orders (k in (12)) were tested using the data labeled with all possible 4 emotions combinations from the 6 subjects who had EEG data with 8 emotions in the DEAP database. The results are shown in Table 4. To save computation time and reduce the size of feature dimension, k=36 is the optimal choice. This choice of k is also consistent with the setting in [55], where the optimal choice of HOC order k is set to 36. After feature extraction, the Support Vector Machine classifier with polynomial kernel implemented by LIBSVM [17] (as described in Section 3.3) was used to classify the data. Since in Experiment 1 and 2, the experiments' duration is relatively shorter than in the DEAP database, 4-fold cross validation was applied.

6 Results and Discussion

After the analysis of the questionnaires, in the DEAP database, we have got EEG data labeled with 8 emotions from 6 subjects, namely Subject 7, 8, 10,

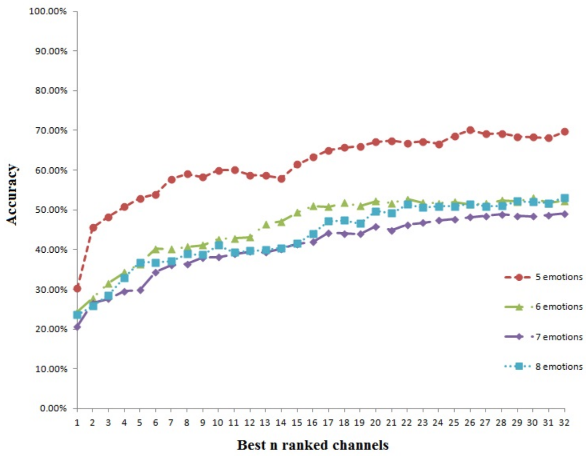

Fig. 4: Mean accuracy of emotions classification of the subjects' data with 5 to 8 emotions.

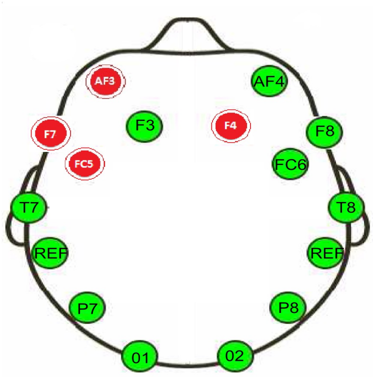

Fig. 5: Positions of the 4 channels (FC5, F4, F7, and AF3).

Table 4: Parameter choice for HOC features.

	$k = 10$	$k = 20$	$k = 36$	$k = 50$
Mean Accuracy	49.76%	49.67%	50.13%	50.15%

16, 19, and 20. For each subject, EEG data from one trial labeled with one of the eight emotions were used in the following processing. In Experiment 1, we have got EEG data labeled with 5 emotions from 1 subject, with 3 emotions from 4 subjects, and with 2 emotions from 6 subjects. In Experiment 2, we have got EEG data labeled with 6 emotions from 2 subjects, with 5 emotions from 1 subject, with 4 emotions from 2 subjects, with 3 emotions from 4 subjects and with 2 emotions from 5 subjects.

Fractal Dimension analysis could be used to quantify the nonlinear property of EEG signals [4]. In this algorithm, we propose to combine FD feature with other best features to improve the classification performance of emotion recognition. Using just 1 FD feature solely has better accuracy than using 6 statistical features or 36 HOC features for some subjects. For example, as it shown in Fig. 6, FD features outperforms the other two types of features in the recognition of NHL and PLL, NHL and NLH, NHL and NLL, PHH and NLH, PLL and NLH for Subject 10; NHL and PHL, NHH and PHH, NHH and PHL for Subject 19 in DEAP database.

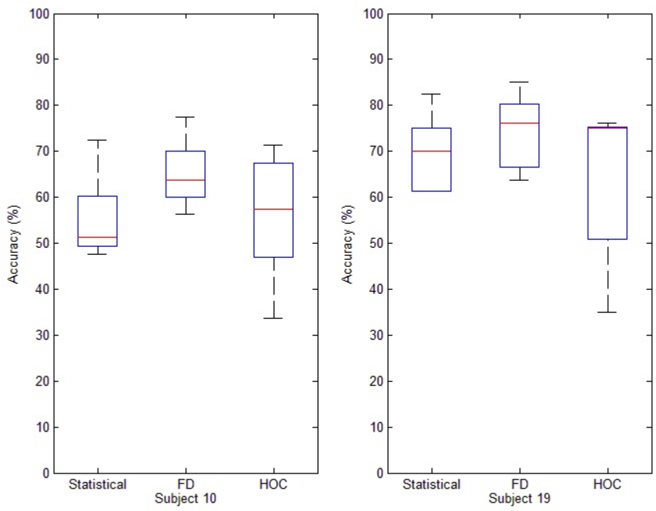

Fig. 6: The comparison of classification accuracies using statistical features, FD, HOC features of Subject 10 and 19.

In Fig. 7, FD values spatial patterns show that FD values can be used to differentiate 8 emotions. Here, the FD values are calculated from 6 subjects in DEAP database who have 8 emotions' data available. The pattern is obtained as follows. First, the FD values are calculated using the 512 sliding window with 75% overlapping from each channel and subject. Then, the calculated values are averaged across all 57 samples of FD values from each channel per emotion. Secondly, the mean FD values are scaled to -1, 1 across all 32 channels for each subject per emotion. Finally, the scaled mean FD values in step 2 are averaged cross all 6 subjects per emotion and visualized on the brain map. As it can be seen from Fig. 7, different emotions have different spatial patterns, and the frontal lobe is always active (in red or yellow). Higher FD values of EEG reflect higher activity of the brain. FD value can be used for differentiation of valence dimension in the Valence-Arousal-Dominance model [47]. It can be seen from Fig. 7 that in negative emotions such as (a) frightened, (b) angry, (g) unconcerned, (h) sad, the spatial pattern shows that the right hemisphere is more active than the left one, and in (a) frightened, (b) angry, the right hemisphere is more active than the right hemisphere in (g) unconcerned and (h) sad emotions. In positive emotions such as (c) happy, (d) surprise, (e) protected, (f) satisfied, the spatial pattern shows that the left semisphere is more active than the right one, and the left hemisphere is more active in (c) happy, (d) surprise than the left hemisphere in (e) protected, (f) satisfied emotions.

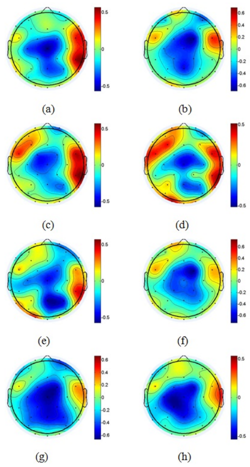

Fig. 7: The visualization of FD pattern for 6 subjects from DEAP with 8 emotions: (a) frightened, (b) angry, (c) happy, (d) surprise, (e) protected, (f) satisfied, (g) unconcerned, and (h) sad.

In Table 5, the comparisons of mean accuracy of the emotion classification for 8 emotions using the data from the DEAP database for combination of HOC, 6 statistical and 1 FD features, combination of 6 Statistical and 1 FD feature, 6 statistical features, and HOC features are shown respectively. The accuracy of fewer emotional states was computed as the mean value for all possible combination of emotions in the group across all subjects. For example, the mean accuracy of 2 out of 8 emotions was calculated as follows. Since we have 8 emotions in total, the 2 emotions combinations could be (PHH and PHL), (PLH and NHH), (PLL and NLL), etc. For each subject, there are 28 possible combinations for choosing 2 emotions from 8 emotions. The mean accuracy over 28 combinations for each subject was calculated, and the mean accuracy over 6 subjects is given in the table. As expected, the classification accuracy increases when the number of emotions recognized is reduced. A one-way ANOVA was performed on the results of the recognition of 4 emotions, and the statistical test was applied to the accuracy by using the combination of HOC, 6 statistical, and FD features and by using other features. As shown in Table 6, the statistical results showed that the proposed combined features when Fractal Dimension feature was included (HOC, 6 statistical and 1 FD) are statistically superior to using solely HOC (p=6.8926e-071) or 6 statistical features (p=0.0056). As can be seen from the Table 5, using the combination of HOC, 6 statistical and 1 FD features has slightly higher accuracy than using the combination of 6 statistical and 1 FD, however, no significant difference is found between these two combined features (p=0.42). Thus, both combinations of features could be used.

Table 5: The classification accuracy computed using the DEAP database.

Feature type	Number of emotions recognized						
	8	7	6	5	4	3	2
HOC+6 statistical +FD	53.7	56.24	59.3	63.07	67.9	74.36	83.73
6statistical +FD	52.66	55.28	58.37	62.2	67.08	73.69	83.2
6 statistical	50.36	53.04	56.19	60.07	65.07	71.9	82
HOC	32.6	35.55	39.23	43.92	50.13	58.88	72.66

Table 6: F-values and p-values of the ANOVA tests applied on the accuracy of proposed combined features (HOC, 6 statistical, FD) and the other features.

Feature	F-value	p-value
Statistical Features	7.72	<0.01
HOC	385.4	<0.01
6statistical, FD	0.44	0.42

We also validated our algorithm on the data from our own databases (Experiment 1 and 2). The results are presented in Table 7 and 8 correspondingly. The accuracy of fewer emotional states is the mean across all subjects who have the data that are labeled with the corresponding number of emotions. For example, the accuracy for 2 emotions recognition in Table 7 is the average across all 11 subjects in Experiment 1 with their corresponding 2 emotions recognition results. The results in Table 7 and 8 also support our conclusion that the combination of HOC, 6 statistical and 1 FD features or 6 statistical features with 1 FD feature is the optimal choice for real-time applications. The algorithm accuracy improves from 68.85% to 87.02% or 86.17% in Experiment 1 and from 63.71% to 76.53% or 76.09% in Experiment 2 when combinations of HOC, 6 statistical and

1 FD features or 6 statistical features and 1 FD feature were used comparing to HOC features. As it can be seen from Table 5, 7, 8, the classification accuracies for the same number of emotions are comparable among three databases, which gives positive support to the use of the proposed algorithm in real-time EEG-based emotion recognition. The computation time to extract one new sample of the combined feature in Matlab is less than 0.1 second and classifying this sample by SVM takes less than 0.05 seconds. Thus the algorithm can be used in real time.

Since the DEAP dataset has up to 32 channels, we also investigated the relationship between the number of channels and the classification accuracy in Table 9. The increasing of the channels follows the channel rank given in Section 5.2. With 32 channels we can improve the accuracy of our algorithm from 53.7% to 69.53% for recognition of 8 emotions and from 83.73% to 90.35% for recognition of 2 emotions.

When comparing our algorithm with others, it can recognize more emotions, obtain better accuracy with fewer electrodes, and it can be used in real time. For example, 32 channels were used in [42] whereas only 4 channels are needed in our algorithm with an accuracy of 87.02% for recognition of 2 emotions and 53.7% for recognition of 8 emotions. Using the same number of channels, [15] achieved 57.04% accuracy for recognition of 2 emotions, which are lower than ours.

Table 7: The classification accuracy computed using Experiment 1 database.

Feature type	Number of emotions recognized			
	5	4	3	2
HOC+6 statistical +FD	61.67	67.08	74.44	87.02
6statistical +FD	55	62.08	75.11	86.17
6 statistical	56.67	61.67	72.72	84.94
HOC	35	42.08	53.17	68.85

Table 8: The classification accuracy computed using Experiment 2 database.

Feature type	Number of emotions recognized				
	6	5	4	3	2
HOC+6 statistical +FD	56.6	60.6	58.36	65.52	76.53
6statistical +FD	59.03	62.08	59.86	65.78	76.09
6 statistical	56.94	62.45	55.78	63.73	76.45
HOC	35.42	42.82	42.46	44.43	63.71

Table 9: Investigation of using more channels in the DEAP database.

Number of channels	Number of emotions recognized						
	8	7	6	5	4	3	2
1	38.33	41.76	45.82	50.76	57.04	65.5	77.98
2	42.03	45.37	49.26	53.95	59.82	67.6	79.06
3	49.27	52.23	55.79	60.12	65.54	72.57	82.53
4	53.7	56.24	59.3	63.07	67.9	74.36	83.73
16	65.63	67.93	70.53	73.58	77.3	82.09	88.79
32	69.53	71.43	73.73	76.53	80	84.41	90.35

7 Conclusion

In this paper, we proposed a real-time subject-dependent algorithm based on the Valence-Arousal-Dominance emotion model. The algorithm can recognize up to 8 emotions such as happy, surprised, satisfied, protected, angry, frightened, unconcerned, and sad with the best average accuracy of 53.7% using 4 electrodes. 2 emotions can be recognized with the best average accuracy of 87.02% using 4 electrodes. The algorithm consists of two parts: features extraction and classification. The combination of features (HOC, 6 statistical and 1 FD) that gave the best emotion classification accuracy was chosen for the algorithm implementation. The algorithm uses just 4 channels that made it more applicable as less time is needed to mount 4 electrodes. The algorithm was tested using two experimental EEG databases with data collected using the Emotiv EPOC device: one with audio stimuli and the other with visual stimuli. It was also tested on the DEAP benchmark database where video stimuli were used for emotion induction. The accuracy of the proposed algorithm was similar on all databases. By using different databases, it is confirmed that the proposed algorithm is device independent as we get similar accuracy using the EEG data collected by two different devices: 14 EEG channels Emotiv Epoch and 32 EEG channels Biosemi ActiveTwo device. It is also confirmed that our algorithm is stimuli independent since our algorithm is tested on the EEG databases created using audio, visual and video stimuli. The channel selection was performed using the DEAP database as it had 32 subjects and combination of audio and visual stimuli, and FC5, F4, F7, and AF3 channels were chosen for our algorithm implementation. The accuracy of the algorithm was tested on all databases following the fixed channel choice. The proposed algorithm can be used in any EEG-enabled applications such as advertising [45], music therapy [65] and other serious games developments [27]. The combination of EEG and other biosignals should be investigated in the future.

Acknowledgments. This research was done for Fraunhofer IDM@NTU, which is funded by the National Research Foundation (NRF) and managed through the multi-agency Interactive & Digital Media Programme Office (IDMPO) hosted by the Media Development Authority of Singapore (MDA).

References

1. Biosemi, http://www.biosemi.com
2. Emotiv, http://www.emotiv.com
3. American electroencephalographic society guidelines for standard electrode position nomenclature. Journal of Clinical Neurophysiology 8(2), 200–202 (1991)
4. Accardo, A., Affinito, M., Carrozzi, M., Bouquet, F.: Use of the fractal dimension for the analysis of electroencephalographic time series. Biological Cybernetics 77(5), 339–350 (1997)
5. Aftanas, L.I., Lotova, N.V., Koshkarov, V.I., Popov, S.A.: Non-linear dynamical coupling between different brain areas during evoked emotions: An EEG investigation. Biological Psychology 48(2), 121–138 (1998)
6. Anderson, E.W., Potter, K.C., Matzen, L.E., Shepherd, J.F., Preston, G.A., Silva, C.T.: A user study of visualization effectiveness using EEG and cognitive load. Computer Graphics Forum 30(3), 791–800 (2011)
7. Arvaneh, M., Cuntai, G., Kai Keng, A., Chai, Q.: Optimizing the channel selection and classification accuracy in EEG-Based BCI. Biomedical Engineering, IEEE Transactions on 58(6), 1865–1873 (2011)
8. Aspiras, T.H., Asari, V.K.: Log power representation of EEG spectral bands for the recognition of emotional states of mind. In: 8th International Conference on Information, Communications and Signal Processing (ICICS) 2011. pp. 1 – 5 (2011)
9. Bechara, A., Damasio, H., Damasio, A.R.: Emotion, decision making and the orbitofrontal cortex. Cerebral Cortex 10(3), 295–307 (2000)
10. Bolls, P.D., Lang, A., Potter, R.F.: The effects of message valence and listener arousal on attention, memory, and facial muscular responses to radio advertisements. Communication Research 28(5), 627–651 (2001)
11. Bos., D.O.: EEG-based emotion recognition (2006), http://hmi.ewi.utwente.nl/verslagen/capita-selecta/CS-Oude_Bos-Danny.pdf
12. Bradley, M.M.: Measuring emotion: The self-assessment manikin and the semantic differential. Journal of Behavior Therapy and Experimental Psychiatry 25(1), 49–59 (1994)
13. Bradley, M.M., Lang, P.J.: The international affective digitized sounds (2nd edition; IADS-2): Affective ratings of sounds and instruction manual. Tech. rep., University of Florida, Gainesville (2007)
14. Burgdorf, J., Panksepp, J.: The neurobiology of positive emotions. Neuroscience & Biobehavioral Reviews 30(2), 173–187 (2006)
15. Cao, M., Fang, G., Ren, F.: EEG-based emotion recognition in chinese emotional words. In: Proceedings of CCIS 2011. pp. 452–456 (2011)
16. Chanel, G., Rebetez, C., Betrancourt, M., Pun, T.: Emotion assessment from physiological signals for adaptation of game difficulty. IEEE Transactions on Systems, Man, and Cybernetics Part A:Systems and Humans 41(6), 1052–1063 (2011)
17. Chang, C.C., Lin, C.J.: LIBSVM : a library for support vector machines (2001), http://www.csie.ntu.edu.tw/~cjlin/libsvm
18. Cristianini, N., Shawe-Taylor, J.: An introduction to Support Vector Machines: and other kernel-based learning methods. Cambridge University Press, New York (2000)
19. D'Alessandro, M., Esteller, R., Vachtsevanos, G., Hinson, A., Echauz, J., Litt, B.: Epileptic seizure prediction using hybrid feature selection over multiple intracranial EEG electrode contacts: a report of four patients. Biomedical Engineering, IEEE Transactions on 50(5), 603–615 (2003)

20. Delorme, A., Makeig, S.: EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of Neuroscience Methods 134(1), 9–21 (2004)
21. Duvinage, M., Castermans, T., Dutoit, T., Petieau, M., Hoellinger, T., Saedeleer, C.D., Seetharaman, K., Cheron, G.: A P300-based quantitative comparison between the emotiv epoc headset and a medical EEG device. In: Proceedings of the 9th IASTED International Conference on Biomedical Engineering. pp. 37–42 (2012)
22. Gao, T., Wu, D., Huang, Y., Yao, D.: Detrended fluctuation analysis of the human EEG during listening to emotional music. J Elect. Sci. Tech. Chin 5, 272–277 (2007)
23. Hadjidimitriou, S., Zacharakis, A., Doulgeris, P., Panoulas, K., Hadjileontiadis, L., Panas, S.: Sensorimotor cortical response during motion reflecting audiovisual stimulation: evidence from fractal EEG analysis. Medical and Biological Engineering and Computing 48(6), 561–572 (2010)
24. Hadjidimitriou, S.K., Zacharakis, A.I., Doulgeris, P.C., Panoulas, K.J., Hadjileontiadis, L.J., Panas, S.M.: Revealing action representation processes in audio perception using fractal EEG analysis. Biomedical Engineering, IEEE Transactions on 58(4), 1120–1129 (2011)
25. Higuchi, T.: Approach to an irregular time series on the basis of the fractal theory. Physica D: Nonlinear Phenomena 31(2), 277–283 (1988)
26. Hosseini, S.A., Khalilzadeh, M.A.: Emotional stress recognition system using eeg and psychophysiological signals: Using new labelling process of EEG signals in emotional stress state. In: Biomedical Engineering and Computer Science (ICBECS), 2010 International Conference on. pp. 1–6. IEEE (2010)
27. Hou, X., Sourina, O.: Emotion-enabled haptic-based serious game for post stroke rehabilitation. In: Proceedings of VRST 2013. pp. 31–34 (2013)
28. Hsu, C.W., Chang, C.C., Lin, C.J.: A practical guide to support vector classification. Tech. rep., National Taiwan University, Taipei (2003)
29. Huang, D., Guan, C., Kai Keng, A., Haihong, Z., Yaozhang, P.: Asymmetric spatial pattern for EEG-based emotion detection. In: Neural Networks (IJCNN), The 2012 International Joint Conference on. pp. 1–7 (2012)
30. Jones, N.A., Fox, N.A.: Electroencephalogram asymmetry during emotionally evocative films and its relation to positive and negative affectivity. Brain and Cognition 20(2), 280–299 (1992)
31. Kandel, E.R., Schwartz, J.H., Jessell, T.M., et al.: Principles of neural science, vol. 4. McGraw-Hill New York (2000)
32. Kedem, B.: Time Series Analysis by Higher Order Crossing. IEEE Press, New York (1994)
33. Khosrowabadi, R., Wahab bin Abdul Rahman, A.: Classification of EEG correlates on emotion using features from gaussian mixtures of eeg spectrogram. In: Information and Communication Technology for the Muslim World (ICT4M), 2010 International Conference on. pp. E102–E107. IEEE (2010)
34. Kil, D.H., Shin, F.B.: Pattern recognition and prediction with applications to signal characterization. AIP series in modern acoustics and signal processing, AIP Press, Woodbury, N.Y. (1996)
35. Koelstra, S., Muhl, C., Soleymani, M., Lee, J.S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., Patras, I.: DEAP: A database for emotion analysis ;using physiological signals. Affective Computing, IEEE Transactions on 3(1), 18–31 (2012)
36. Koelstra, S., Muhl, C., Soleymani, M., Lee, J.S., Yazdani, A., Ebrahimi, T., Pun, T., Nijholt, A., Patras, I.: DEAP dataset (2012), `http://www.eecs.qmul.ac.uk/mmv/datasets/deap`

37. Kringelbach, M.L.: The human orbitofrontal cortex: Linking reward to hedonic experience. Nature Reviews Neuroscience 6(9), 691–702 (2005)
38. Kulish, V., Sourin, A., Sourina, O.: Analysis and visualization of human electroencephalograms seen as fractal time series. Journal of Mechanics in Medicine and Biology, World Scientific 26(2), 175–188 (2006)
39. Kulish, V., Sourin, A., Sourina, O.: Human electroencephalograms seen as fractal time series: Mathematical analysis and visualization. Computers in Biology and Medicine 36(3), 291–302 (2006)
40. Lal, T.N., Schroder, M., Hinterberger, T., Weston, J., Bogdan, M., Birbaumer, N., Scholkopf, B.: Support vector channel selection in BCI. Biomedical Engineering, IEEE Transactions on 51(6), 1003–1010 (2004)
41. Lang, P., Bradley, M., Cuthbert, B.: International affective picture system (IAPS): Affective ratings of pictures and instruction manual. technical report a-8. Tech. rep., University of Florida, Gainesville, FL. (2008)
42. Lin, Y.P., Wang, C.H., Jung, T.P., Wu, T.L., Jeng, S.K., Duann, J.R., Chen, J.H.: EEG-based emotion recognition in music listening. IEEE Transactions on Biomedical Engineering 57(7), 1798–1806 (2010)
43. Liu, Y., Sourina, O., Nguyen, M.K.: Real-time EEG-based human emotion recognition and visualization. In: Proc. 2010 Int. Conf. on Cyberworlds. pp. 262–269. Singapore (2010)
44. Liu, Y., Sourina, O., Nguyen, M.K.: Real-time eeg-based emotion recognition and its applications. Transactions on Computational Science XII, LNCS 6670, 256–277 (2011)
45. Liu, Y., Sourina, O.: EEG-based emotion-adaptive advertising. In: Proc. ACII 2013. pp. 843–848. Geneva (2013)
46. Liu, Y., Sourina, O.: EEG databases for emotion recognition. In: Proc. 2013 Int. Conf. on Cyberworlds. Japan (2013)
47. Liu, Y., Sourina, O.: Real-time fractal-based valence level recognition from EEG. In: Transactions on Computational Science XVIII, pp. 101–120. Springer (2013)
48. Lutzenberger, W., Elbert, T., Birbaumer, N., Ray, W.J., Schupp, H.: The scalp distribution of the fractal dimension of the EEG and its variation with mental tasks. Brain Topography 5(1), 27–34 (1992)
49. Maragos, P., Sun, F.K.: Measuring the fractal dimension of signals: morphological covers and iterative optimization. IEEE Transactions on Signal Processing 41(1), 108–121 (1993)
50. Mauss, I.B., Robinson, M.D.: Measures of emotion: A review. Cognition and Emotion 23(2), 209–237 (2009)
51. Mehrabian, A.: Framework for a comprehensive description and measurement of emotional states. Genetic, social, and general psychology monographs 121(3), 339–361 (1995)
52. Mehrabian, A.: Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in temperament. Current Psychology 14(4), 261–292 (1996)
53. Noble, W.S.: What is a support vector machine? Nat Biotech 24(12), 1565–1567 (2006)
54. O'Regan, S., Faul, S., Marnane, W.: Automatic detection of EEG artefacts arising from head movements. In: Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE. pp. 6353–6356 (2010)
55. Petrantonakis, P.C., Hadjileontiadis, L.J.: Emotion recognition from EEG using higher order crossings. IEEE Transactions on Information Technology in Biomedicine 14(2), 186–197 (2010)

56. Petrantonakis, P.C., Hadjileontiadis, L.J.: Adaptive emotional information retrieval from EEG signals in the time-frequency domain. IEEE Transactions on Signal Processing 60(5), 2604–2616 (2012)
57. Picard, R.W., Vyzas, E., Healey, J.: Toward machine emotional intelligence: Analysis of affective physiological state. IEEE Transactions on Pattern Analysis and Machine Intelligence 23(10), 1175–1191 (2001)
58. Pradhan, N., Narayana Dutt, D.: Use of running fractal dimension for the analysis of changing patterns in electroencephalograms. Computers in Biology and Medicine 23(5), 381–388 (1993)
59. Ranky, G.N., Adamovich, S.: Analysis of a commercial EEG device for the control of a robot arm. In: Bioengineering Conference, Proceedings of the 2010 IEEE 36th Annual Northeast. pp. 1–2 (2010)
60. Russell, J.A.: Affective space is bipolar. Journal of Personality and Social Psychology 37(3), 345–356 (1979)
61. Schaaff, K., Schultz, T.: Towards emotion recognition from electroencephalographic signals. In: Affective Computing and Intelligent Interaction and Workshops, 2009. ACII 2009. 3rd International Conference on. pp. 1–6 (2009)
62. Soleymani, M., Pantic, M., Pun, T.: Multimodal emotion recognition in response to videos. IEEE Transactions on Affective Computing 3(2), 211–223 (2012)
63. Sourina, O., Kulish, V.V., Sourin, A.: Novel tools for quantification of brain responses to music stimuli. In: Proc of 13th International Conference on Biomedical Engineering ICBME 2008. pp. 411–414 (2008)
64. Sourina, O., Liu, Y.: A fractal-based algorithm of emotion recognition from EEG using arousal-valence model. In: BIOSIGNALS. pp. 209–214 (2011)
65. Sourina, O., Liu, Y., Nguyen, M.K.: Real-time EEG-based emotion recognition for music therapy. Journal on Multimodal User Interfaces 5(1-2), 27–35 (2012)
66. Sourina, O., Sourin, A., Kulish, V.: EEG data driven animation and its application. In: Computer Vision/Computer Graphics CollaborationTechniques. pp. 380–388. Springer (2009)
67. Stam, C.J.: Nonlinear dynamical analysis of EEG and MEG: Review of an emerging field. Clinical Neurophysiology 116(10), 2266–2301 (2005)
68. Stytsenko, K., Jablonskis, E., Prahm, C.: Evaluation of consumer EEG device Emotiv EPOC. In: Poster session presented at MEi:CogSci Conference 2011. Ljubljana (2011)
69. Szily, E., Kéri, S.: Emotion-related brain regions. Ideggyógyászati szemle 61(3-4), 77 (2008)
70. Takahashi, K.: Remarks on emotion recognition from multi-modal bio-potential signals. In: Industrial Technology, 2004 IEEE International Conference on. vol. 3, pp. 1138–1143 (2004)
71. Vecchiato, G., Toppi, J., Astolfi, L., De Vico Fallani, F., Cincotti, F., Mattia, D., Bez, F., Babiloni, F.: Spectral EEG frontal asymmetries correlate with the experienced pleasantness of tv commercial advertisements. Medical and Biological Engineering and Computing 49(5), 579–583 (2011)
72. Wang, Q., Sourina, O., Nguyen, M.K.: EEG-based "serious" games design for medical applications. In: Proc. 2010 Int. Conf. on Cyberworlds. pp. 270–276. Singapore (2010)
73. Wang, Q., Sourina, O., Nguyen, M.: Fractal dimension based neurofeedback in serious games. The Visual Computer 27(4), 299–309 (2011)
74. Zhang, Q., Lee, M.: Analysis of positive and negative emotions in natural scene using brain activity and gist. Neurocomputing 72(4-6), 1302–1306 (2009)