# EEG Databases for Emotion Recognition

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***Abstract*— Emotion recognition from Electroencephalogram (EEG) rapidly gains interest from research community. Two affective EEG databases are presented in this paper. Two experiments are conducted to set up the databases. Audio and visual stimuli are used to evoke emotions during the experiments. The stimuli are selected from IADS and IAPS databases. 14 subjects participated in each experiment. Emotiv EEG device is used for the data recording. The EEG data are rated by the participants with arousal, valence, and dominance levels. The correlation between powers of different EEG bands and the affective ratings is studied. The results agree with the literature findings and analyses of benchmark DEAP database that proves the reliability of the two databases. Similar brain patterns of emotions are obtained between the established databases and the benchmark database. A SVM-based emotion recognition algorithm is proposed and applied to both databases and the benchmark database. Use of a Fractal Dimension feature in combination with statistical and Higher Order Crossings (HOC) features gives us results with the best accuracy. Up to 8 emotions can be recognized. The accuracy is consistent between the established databases and the benchmark database.**

***Keywords- EEG; affective database; emotion recognition; fractal dimension; affective computing***

## I. INTRODUCTION

Emotion is a mental state and an affective reaction towards an event based on subjective experience [1]. It is essential to the human's daily communication and behaviors. Normally, we identify others' emotions by their facial expressions, voice or body language. However, as the facial expressions, voice or body movements can be intended, if we need to know the inner emotion, Electroencephalogram (EEG) is one of the methods to recognize the emotion. Additionally, EEG-based emotion recognition could make the human computer interface more intelligent and could be applied in many fields such as E-learning, games and even marketing.

The emotion classification systems include discrete and dimensional ones. Plutchik proposed eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance, and joy [2]. Ekman revealed the relationship between facial expressions and emotions. In his theory, there are six emotions associated with facial expressions: anger, disgust, fear, happiness, sadness and surprise. Later he expanded the basic emotions by adding amusement, contempt, contentment, embarrassment, excitement, guilt, pride in achievement, relief, satisfaction, sensory pleasure, and shame [3]. From the dimensional perspective, the most widely used classification is the bipolar model - valence and arousal dimensions advocated by Russell [4]. Valence represents the quality of an emotion, ranging from unpleasant to pleasant. Arousal denotes the quantitative activation level, from not aroused to aroused. Later a three-dimensional Pleasure-Arousal-Dominance (PAD) model was proposed by Mehrabian and Russell in [5] and [6]. In this model, besides the arousal and valence dimensions, an additional dimension called dominance is added, which is also named as the control dimension of emotion [5] [6]. It ranges from a feeling of being in control during an emotional experience to a feeling of being controlled by the emotion [7]. It makes the dimensional models more complete. With the help of the third emotional dimension, more emotion labels can be located in the 3D space. For example, anger and fear are both high arousal and negative states, but the dominance level of anger is higher than fear. In this work, we use the valence, arousal and dominance dimensional model.

Currently, the existing EEG databases are mostly about motor imaginary, sleep stages, mental tasks and epileptic. For example, [8] has published a number of EEG databases that are related to hands, feet, and tongue motor imagery and P300 speller paradigm; 9736 polysomnograms are available in [9]; the EEG data recorded during various mental tasks are released in [10]; the EEG data from both epileptic patient and normal subjects are published in [11].

So far there are only a few affective EEG databases published. To our best knowledge, merely 3 affective EEG databases could be downloaded from the Internet. The first one is the eNTERFACE database [12], the second one is the DEAP database [13], and the third one is the database established by Yazdani et al [14]. eNTERFACE Project 7 "Emotion Detection in the Loop from Brain Signals and Facial Images" can be found in [12]. The stimuli used are IAPS pictures, and the targeted emotions are calm, exciting positive and exciting negative. Five subjects participated in the data recording. Although a Biosemi Active 2 acquisition system [15] with 64 EEG channels and sampling rate 1024 Hz was used, due to the occlusion from fNIRS sensor arrangement, data from ten frontal electrodes: F5, F8, AF7, AF8, AFz, Fp1, Fp2, Fpz, F7, and F6 are removed and data from the remained 54 channels are advised to be used. The DEAP database based on Valence-Arousal-Dominance emotion model is available in [13]. It has a large amount of

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subjects (32 subjects) who participated in the data collection. The stimuli to elicit emotions in the experiment are one-minute long music videos. In total 40 music videos are used. In the DEAP database, a 32 EEG channels Biosemi ActiveTwo device [16] was used in the data recording. The sampling rate is 512 Hz. All recorded data are labeled with the corresponding arousal, valence, dominance, and like/dislike values (ranging from 1 to 9). There are different datasets available in DEAP database. For example, the original EEG dataset, the videos dataset which records the subjects' facial expressions, the preprocessed EEG data, etc [17]. More details about the DEAP database could be found in [13] and [17]. [14] contains affective EEG and peripheral data which were collected from 6 participants. Music videos are used to invoke emotions and the two-dimensional arousal-valence model together with like/dislike ratings were employed in the self-assessment rating. The data are collected by an EEG device with 32 active AgCl electrodes at a sampling rate of 512 Hz.

In this paper, two databases are set up. The first one uses the sound clips from IADS database [18] as the audio stimuli to evoke emotions. The second one uses the pictures from IAPS database [19] as the visual stimuli. 14 subjects participated in both experiments, and their EEG data were recorded using the 14 channels Emotiv Epoch device [20]. The data are labeled with arousal, valence and dominance ratings by the subjects using Self-Assessment Manikin (SAM) [21]. The databases established by us have 14 subjects participated in both data collections, and the stimuli are different for both databases (one with audio and the other with visual ones). To our best knowledge, there is no EEG database that is collected with Emotiv Epoch, labeled with arousal, valence and dominance ratings and emotions evoked by different types of stimuli. Affective EEG databases with different stimuli such as visual and audio are needed to be set up for future research in the emotion processing and brain computer interface field. By using these databases, we show the spatial pattern of the subjects during emotion processing and compare it with the one of the benchmark DEAP database.

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 [22]. 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 [23]. At the same year, [24] and [25] 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 [26], and in [27], both algorithms were applied to recognize high/low arousal and positive/negative valence [27]. In [28], a fractal based valence levels recognition algorithm was proposed and elaborated in [29]. In this paper, we propose to use a FD feature in combination with statistical and Higher Order Crossings (HOC) to improve SVM-based emotion recognition algorithms 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 HOC features gives the results with the best accuracy with adequate computational time. The features' values are calculated from EEG using a sliding window. The results show that all three databases have similar accuracies.

The paper is organized as follows. In Section II, the stimuli selection including the introduction of IADS and IAPS databases are given. In Section III, the detail of experiments setup is described. In Section IV, the analysis of the self-assessment questionnaire is presented. In Section V, the correlation between EEG and the affective ratings is studied. In Section VI, the visualizations of FD-based spatial pattern for happy and frightened emotions are given. In Section VII, the results of SVM-based classification for up to 8 emotions recognition is presented. Section VIII concludes the paper.

## II. Experiment Stimuli Selection

### A. *IADS and IAPS Database*

The International Affective Picture System (IAPS) [19] and the International Affective Digitized Sound system (IADS) [18] are developed and distributed by the NIMH Center for Emotion and Attention (CSEA) at the University of Florida. IAPS intends to provide a set of standardized, emotionally visual stimuli, while IADS provides a set of acoustic emotional stimuli. Both of them are aimed at setting up stimuli databases for experimental investigations of emotion and attention.

The IAPS database contains color photos from a different areas, and all photos are labeled with the valence, arousal and dominance level ratings which were assessed by a large number of subjects [19]. The IADS was created the same way as the IAPS database but with rated sounds clips [18]. The rating values range from 1 to 9 for all emotional dimensions. For arousal level, rating value 1 indicates the calmest state, and rating value 9 indicates the most excited state; for valence level, value 1 denotes the most negative state, and value 9 denotes the most positive state; for dominance level, rating value 1 represents the feeling of fully controlled by the surroundings; and value 9 represents the feeling of full control of the surroundings.

### B. *Stimuli Selection Criteria*

In our audio experiment, emotions are induced by playing the sound clips selected from the IADS. In our visual experiment, emotions are elicited with visual stimuli selected from IAPS database. The sound clips/pictures are selected based on their assessed Arousal, Valence and Dominance dimension values given in IADS and IAPS databases. Only sound clips/ pictures with the extreme values in each dimension were chosen in order to guarantee the successful elicitation of the targeted emotions.

In the audio experiment, according to the sounds clips' location in the Arousal, Valence and Dominance 3-dimensional map, 40 clips are chosen to induce eight emotional states, namely Positive/ Low arousal /Low dominance (PLL) "protected", Positive/ Low arousal /High dominance (PLH) "satisfied", Positive/ High arousal/ Low dominance (PHL) "surprise", Positive/ High arousal/ High dominance (PHH) "happy", Negative/ Low arousal /Low dominance (NLL) "sad", Negative/ Low arousal /High dominance (NLH) "unconcerned", Negative/ High arousal /Low dominance (NHL) "frightened", and Negative/ High arousal /High dominance (NHH) "angry". Since the authors of IADS and IAPS do not allow publishing pictures (stimuli) of IADS and IAPS in scientific journals or any other publication, we provide only the numbers of the stimuli used in our experiments as they recommended. The sound clips with the corresponding numbers were chosen from IADS for each session as follows. Session 1: 170, 262, 368, 602, 698 were chosen to induce PLL, Session 2: 171, 172, 377, 809, 812 were chosen to induce PLH, Session 3: 114, 152, 360, 410, 425 were chosen to induce PHL, Session 4: 367, 716, 717, 815, 817 were chosen to induce PHH, Session 5: 250, 252, 627, 702, 723 were chosen to induce NLL, Session 6: 246, 358, 700, 720, 728 were chosen to induce NLH, Session 7: 277, 279, 285, 286, 424 were chosen to induce NHL, and Session 8: 116, 243, 280, 380, 423 were chosen to induce NHH.

In the visual experiment, 32 pictures were chosen to induce eight emotional states, namely PLL, PLH, PHL, PHH, NLL, NLH, NHL, and NHH. The details of stimuli targeting emotions in each session are given as follow. Session 1: PLL and the corresponding pictures chosen in IAPS include 7632, 5890, 5982, and 7497. Session 2: PLH and the corresponding pictures chosen in IADS include 5000, 1604, 2370, and 5760. Session 3: PHL and the corresponding pictures chosen in IAPS include 5260, 1650, 8400, and 849. Session 4: PHH and the corresponding pictures chosen in IAPS include 5626, 8034, 8501, and 8200. Session 5: NLL and the corresponding pictures chosen in IAPS include 2682, 2753, 9010, and 9220. Session 6: NLH and the corresponding pictures chosen in IAPS include 2280, 7224, 2810, and 9832. Session 7: NHL and the corresponding pictures chosen in IAPS include 6230, 6350, 9410, and 9940. Session 8: NHH and the corresponding pictures chosen in IAPS include 2458, 3550.2, 2130, and 7360.

## III. Experiment Setup

### A. EEG Device

In all experiments, we used Emotiv [20] device with 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 standardized by the American Electroencephalographic Society [30] (plus CMS/DRL as references) (Fig. 1). 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 wireless receiver. The use of Emotiv device has become popular in the EEG-based research [31] [32]. The reliability and validity of Emotiv device were tested in [33] [34]. Comparison between EEG data recorded from standard EEG device [35] and Emotiv was done, and it showed that the Emotiv device could be a substitution of the standard EEG device in real-time applications where fewer electrodes were needed [33], and it is creditable to be used in games [34].

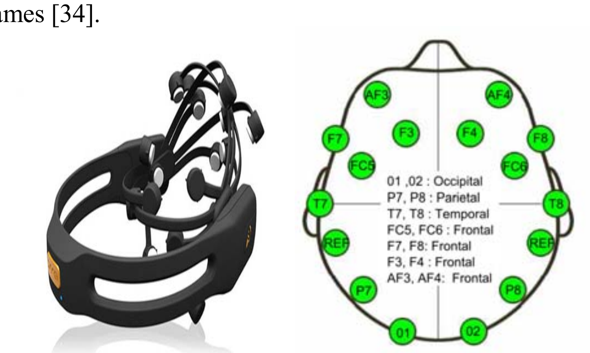



Figure 1. Emotiv device and its electrodes locations [20].

### B. Experiment Protocol

In the audio stimuli experiment, the design of each session is shown in Fig. 2. First, 12 seconds of silence was given to the subject, and then, followed by 5 sound clips. Each clip lasted for 6 seconds. The total duration of one session was 42 seconds plus the self assessment time.

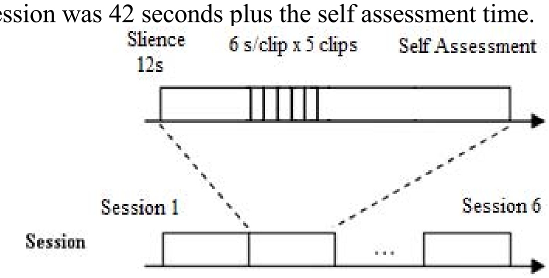



Figure 2. The procedure of audio stimuli experiment.

In the visual stimuli experiment, the design of each session is shown in Fig. 3. First, a black screen was shown to the participant (3 seconds). Second, a white cross in the center of the screen was given to inform the subject that visual stimulus would be shown (4 seconds). Thirdly, the pictures were shown to the subject (4 pictures x 10 seconds/clip=40 seconds). Fourthly, black screen was presented to the participant again (3 seconds). Finally, self-assessment using the questionnaire was done. In summary, each session lasted for 50 seconds plus the self-assessment time.

| Black Screen | "+ "Cross | Picture 1 | Picture 2 | Picture 3 | Picture 4 | Black Screen |
|---|---|---|---|---|---|---|
| 3s | 4s | 10s | 10s | 10s | 10s | 3s |

Figure 3. The procedure of visual stimuli experiment.

## C. *Self-assessment Questionnaire*

The subjects needed to complete the questionnaires after the exposure to the stimuli. The Self-Assessment Manikin (SAM) [21] is a non-verbal pictorial assessment to evaluate emotions. In the audio and visual stimuli experiments, the SAM using the 3D model with valence, arousal and dominance dimensions, and nine levels indicating the intensity in all dimensions (Fig. 4) was employed. The subjects were also asked to describe their feelings in any words including happy, surprised, satisfied, protected, angry, fear, unconcerned, sad or any other emotions.

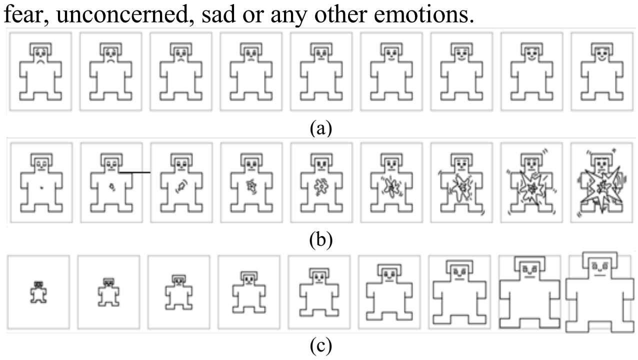



Figure 4. SAM questionnaire for experiments : (a) valence dimension levels; (b) arousal dimension levels; (c) dominance dimension levels [21].

# IV. Analysis of Self-assessment Rating

The self-assessment rating can be analyzed based on the users' needs. For example, if positive/low arousal/high dominance data are needed, the self-assessment rating 5 could be used as the threshold. As a result, the EEG data labelled with valence rating larger than 5, arousal rating smaller than 5, dominance rating larger than 5 are the required one.

# V. Correlation between EEG and Ratings

To study the correlation between EEG and affective ratings, we follow the processing in [13]. First, the raw data are filtered by a 2Hz High-pass filter. The EEG data collected from the entire 30 seconds' exposure to audio stimuli and the first 30 seconds' exposure to visual stimuli are considered as the data with emotions. The EEG data recorded from the 5 seconds before the exposure to stimuli are used as baseline to remove the emotion-irrelevant variations in power.

A 3 to 47 Hz filter with Welch's method (window size of 256 samples) is applied to both data with emotion and baseline. Then the baseline power is subtracted from the data with emotion. By doing this, it allows us to obtain the relative change of power during the exposure to stimuli. After that, the mean changes of power from theta (3-7Hz), alpha (8-13Hz), beta (14-29Hz) and gamma (30-47Hz) are computed. The Spearman correlation coefficients between the power changes and the self-assessment ratings from each subject are calculated. The corresponding p-values per subject are finally combined to one p-value following Fisher's method [36] [37].

The details about the electrodes with significant correlation ($p<0.05$) is given in Table I (electrodes obtained from visual and audio experiment are put together). In Table I, $\overline{R}$ denotes the mean correlation between the power changes and the subjective ratings across all subjects from visual or audio experiment, $R^{+}$ denotes the most positive correlations, and $R^{-}$ denotes the most negative correlations.

For arousal dimension, we find negative correlations in theta, beta, and gamma band. It means that an increase of arousal leads to a decrease of theta, beta, and gamma powers. Although we don't have central channels as in DEAP database, we obtained negative correlation in beta band of frontal electrodes (F4 and F8 in Table I), which is compatible with the findings in DEAP database [13]. In [13], it is found that beta band of electrodes FC2 has a negative correlation with arousal.

For valence dimension, we get a positive correlation in beta band and a negative correlation in gamma band. It means that an increase of valence leads to an increase of beta power and a decrease of gamma power. The findings that beta band of frontal electrode (F4 in Table I) has a positive correlation with valence is compatible with the one in DEAP. In [13], it shows that frontal electrode FC6 has a positive correlation with valence.

For dominance dimension, we find that the beta band of the frontal lobe electrode FC5 has a positive correlation with dominance levels. It means that an increase of dominance lead to an increase of beta power of electrode FC5.

# VI. Fractal Dimension-based Spatial Pattern

In Section V, we showed the correlation between the 3D emotional ratings and the power of different EEG bands. All the data were used in the correlation analysis. In this Section, we study the spatial pattern of EEG with discrete emotion labels using fractal dimension value calculated based on Higuchi Fractal Dimension algorithm [38]. A special case of happy and frightened emotions are investigated in the visualization. Since happy is a positive, high arousal, high dominance emotion and frightened is a negative, high arousal, low dominance emotion, rating 5 is used as the threshold to determine high/low arousal, positive/negative valence and high/low dominance. The data of two subjects who have EEG data labelled with happy and frightened emotions in the audio and visual experiments are used to illustrate the spatial pattern.

## A. *Spatial pattern of Fractal Dimension*

To obtain the pattern, we process the EEG data as follows. First, the raw data are filtered by a 2-42 Hz band-pass filter, then FD values are calculated using a 512 sliding window with 75% overlapping from the filtered data of each channel per subject. Next, the calculated values are averaged across all FD values from each channel per emotion. Finally the mean FD values are scaled to -1, 1 across all 14 channels per emotion and visualized on the brain map. The visualizations are given in Fig. 5 and 6 for the audio and visual experiment respectively.

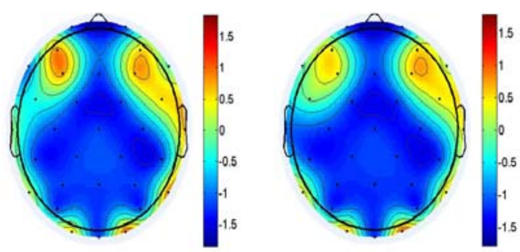
TABLE I. THE ELECTRODES WITH SIGNIFICANT CORRELATIONS.

| | Theta | | | | Alpha | | | | Beta | | | | Gamma | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Elec** | $\overline{R}$ | $R^-$ | $R^+$ | **Elec** | $\overline{R}$ | $R^-$ | $R^+$ | **Elec** | $\overline{R}$ | $R^-$ | $R^+$ | **Elec** | $\overline{R}$ | $R^-$ | $R^+$ |
| **Arousal** | T8 | -0.1 | -0.86 | 0.93 | | | | | P8 | 0.13 | -0.67 | 0.84 | T8 | -0.01 | -0.77 | 0.92 |
| | | | | | | | | | T8 | -0.02 | -0.89 | 0.78 | | | | |
| | | | | | | | | | F4 | -0.06 | -0.73 | 0.8 | | | | |
| | | | | | | | | | F8 | -0.08 | -0.79 | 0.81 | | | | |
| **Valence** | | | | | | | | | F4 | 0.03 | -0.69 | 0.9 | P7 | -0.23 | -0.86 | 0.78 |
| **Dominance** | | | | | | | | | FC5 | 0.03 | -0.95 | 0.75 | | | | |

In Fig. 5, the spatial patterns show that FD values can be used to differentiate 2 emotions in the audio experiment. As it can be seen from Fig. 5, happy and frightened emotions have different spatial patterns but the frontal lobe is always active. Higher FD values of EEG reflect higher activity of the brain. FD values can be used to differentiate valence dimension in the Valence-Arousal-Dominance model. In Fig. 5, it shows that the right hemisphere of negative emotions (fear) is more active than the left one. On the other hand, the positive emotions (happiness) have a more active left hemisphere than negative ones.

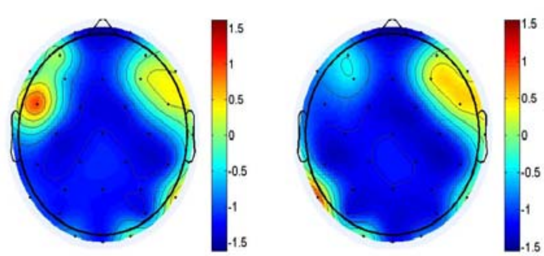
In Fig. 6, the pattern of visual experiment is similar to the one of audio experiment. Again, it can be seen from Fig. 6 that negative emotions (fear) has a more active right hemisphere than the left one.

Additionally, we can see that although there are fewer channels in our database, the pattern that right hemisphere is more active when feeling negative is consistent with the pattern obtained from DEAP database (Fig. 7).



(a) (b)

Figure 5. The visualization of FD pattern for 1 subject from audio experiment with 2 emotions: (a) Happy (PHH) (b) Frightened (NHL).



(a) (b)

Figure 6. The visualization of FD pattern for 1 subject from visual experiment with 2 emotions: (a) Happy (PHH) (b) Frightened (NHL).

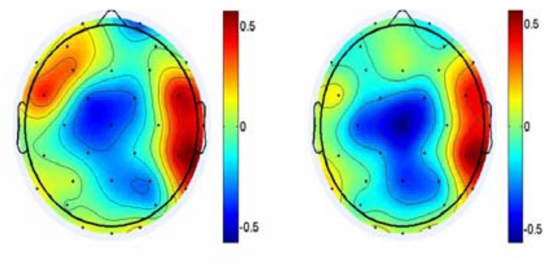


Figure 7. The visualization of FD pattern for 1 subject from DEAP experiment with 2 emotions: (a) Happy (PHH) (b) Frightened (NHL).

## VII. SVM-BASED ALGORITHM

In this section, we present a subject-dependent algorithm of human emotion recognition from EEG based on the Valence-Arousal-Dominance emotion model and apply it to our databases and DEAP database. 8 emotions defined by the combinations of high/low arousal levels, positive/negative valence levels, and high/low dominance levels are targeted to be identified. After analyzing the self-assessment questionnaire, in the audio experiment, 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 visual experiment, 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. In the DEAP database, we have EEG data labeled with 8 emotions from 6 subjects, namely Subject 7, 8, 10, 16, 19, and 20.

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 the first part, a 2-42 Hz bandpass filter was applied to the data since it could remove artifacts such as muscle contraction and control [24] [39]. We used the DEAP database and Fisher Discrinant Ratio method [40] for channel selection. 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 top 4 channels FC5, F4, F7, and AF3 channels were chosen for the algorithm implementation. The feature vector $\boldsymbol{FV}$ for emotion classification is defined as follows:

$$\boldsymbol{FV} = [\boldsymbol{FV_1}, \boldsymbol{FV_2}, \boldsymbol{FV_3}, \boldsymbol{FV_4}]. \quad (1)$$

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 solely the Higuchi Fractal Dimension features [38], HOC [41], statistical features [42], or the combinations of different features $\boldsymbol{FV_{comb1}}$ and $\boldsymbol{FV_{comb2}}$ as given below in (2) and (3). Normalization is applied to the FD, statistical features and HOC features across the four channels in (1).

$$\boldsymbol{FV_{comb1}} = [\mu_X, \sigma_X, \delta_X, \overline{\delta_X}, \gamma_X, \overline{\gamma_X}, \dim_H]. \quad (2)$$

$$\boldsymbol{FV_{comb2}} = [D_1, \ldots, D_k, \mu_X, \sigma_X, \delta_X, \overline{\delta_X}, \gamma_X, \overline{\gamma_X}, \dim_H] \quad (3)$$

Here, $\boldsymbol{FV_{comb1}}$ employs 6 statistical and 1 FD features, $\boldsymbol{FV_{comb2}}$ employs HOC features, 6 statistical and 1 FD features. In (2) and (3), normalization is applied to the statistical features, HOC features, and FD features across the four channels before combining the features. A sliding window with the size of 512 with 384 samples overlapping was used to calculate the statistical features, HOC features, and the combined features.

The second part is the SVM-based classification: a SVM classifier implemented by LIBSVM [43] with polynomial kernel for multiclass classification was used to recognize emotions. A grid-search approach was applied to select the SVM kernel parameters, based on the classification accuracy of emotion recognition, the parameters of the SVM classifier were set as follows: the value of $gamma$ was set to 1, $coef$ was set to 1 and order $d$ was set to 5. 4-fold cross validation is applied to our database and 5-fold cross validation is applied to DEAP database since it has more samples.

The results are presented in Table II and III for audio and visual experiment respectively. The accuracy of fewer emotional states was computed as the mean value for all possible combinations of emotions in the group across all subjects. For example, the accuracy for 2 emotions recognition in Table II is calculated like this: first, the mean accuracy over all combinations of two emotions was calculated and averaged for each subject, and then the mean accuracy over 11 subjects in the audio experiment is given in the table.

The results in Table II and III shows that the combination of HOC, 6 statistical and 1 FD features or 6 statistical features with 1 FD feature is the optimal choice to recognize emotions. The algorithm accuracy improves from 68.85% to 87.02% or 86.17% in audio experiment and from 63.71% to 76.53% or 76.09% in visual experiment when combinations of HOC, 6 statistical and 1 FD features or 6 statistical features and 1 FD feature were used comparing to HOC features. Additionally, the classification accuracy increases when the number of emotions recognized is reduced as expected. As it can be seen from Table II and III, the classification accuracies for the same number of emotions are comparable between two databases, which give positive support to the reliability of the established databases.

We also apply the emotion recognition on the benchmark database DEAP. The mean accuracies of the emotion classification for up to 8 emotions using DEAP are shown In Table IV. As can be seen from the Table IV, using the combination of HOC, 6 statistical and 1 FD features has the highest accuracy, and the accuracy of combination of 6 statistical and 1 FD is similar to it. The results are compatible with the ones obtained from our own databases.

A one-way ANOVA was performed on the results of the recognition of 4 emotions from DEAP database, 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 V, 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 IV, 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).

TABLE II. THE CLASSIFICATION ACCURACY COMPUTED USING AUDIO EXPERIMENT DATABASE

| Feature type | Mean Accuracy (%) | | | |
|---|---|---|---|---|
| | Number of emotions | | | |
| | 5 | 4 | 3 | 2 |
| HOC+6 statistical +FD | 61.67 | 67.08 | 74.44 | 87.02 |
| 6 statistical +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 III. THE CLASSIFICATION ACCURACY COMPUTED USING VISUAL EXPERIMENT DATABASE

| Feature type | Mean Accuracy (%) | | | | |
|---|---|---|---|---|---|
| | Number of emotions | | | | |
| | 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 IV. THE CLASSIFICATION ACCURACY COMPUTED USING THE DEAP DATABASE

| Feature type | Mean Accuracy (%) 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 V. F-VALUES AND P-VALUES OF THE ANOVA TESTS APPLIED ON THE ACCURACY

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

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 VI. The increasing of the channels follows the channel rank given at the beginning of this section. 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.

TABLE VI. INVESTIGATION OF USING MORE CHANNELS IN THE DEAP DATABASE

| Number of channels | Mean Accuracy (%) 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 |

## VIII. CONCLUSION

In this paper, we set up two EEG databases for emotion recognition. In total 28 subjects (14 subjects per experiment) participated in the data recording. Audio stimuli from IADS and visual stimuli from IAPS were chosen to evoke emotions. The recorded EEG data are labeled with arousal, valence and dominance ratings by the self-assessment questionnaire from the subjects. The correlations between the power of different EEG bands and the participants' rating are studied. The correlation between the subjects' rating and their EEG signals in our databases is compatible with the literature findings, which proves the reliability of the established databases. The spatial patterns of happy and frightened emotions are visualized based on fractal dimension values. Comparison with the benchmark database is also given. It shows that right hemisphere is more activated during negative emotion (fear) than positive emotion (happiness). The patterns are stimuli independent. We proposed a real-time subject-dependent algorithm based on the Valence-Arousal-Dominance emotion model and tested it on our own databases and the benchmark database. 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. 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 or 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 average accuracy of the algorithm tested on all databases is consistent.

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