Real-Time EEG-Based Human Emotion Recognition and Visualization

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Real-time EEG-based Human Emotion Recognition and Visualization

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Abstract—**Emotions accompany everyone in the daily life, playing a key role in non-verbal communication, and they are essential to the understanding of human behavior. Emotion recognition could be done from the text, speech, facial expression or gesture. In this paper, we concentrate on recognition of "inner" emotions from electroencephalogram (EEG) signals as humans could control their facial expressions or vocal intonation. The need and importance of the automatic emotion recognition from EEG signals has grown with increasing role of brain computer interface applications and development of new forms of human-centric and human-driven interaction with digital media. We propose fractal dimension based algorithm of quantification of basic emotions and describe its implementation as a feedback in 3D virtual environments. The user emotions are recognized and visualized in real time on his/her avatar adding one more so-called "emotion dimension" to human computer interfaces.**

Keywords- emotion recognition; EEG; emotion visualization; fractal dimension; HCI; BCI

I. INTRODUCTION

Nowadays, new forms of human-centric and human-driven interaction with digital media have the potential of revolutionising entertainment, learning, and many other areas of life. Since emotions play an important role in the daily life of human beings, the need and importance of automatic emotion recognition has grown with increasing role of human computer interface applications. Emotion recognition could be done from the text, speech, facial expression or gesture. Recently, more researches were done on emotion recognition from EEG [1-6]. Traditionally, EEG-based technology has been used in medical applications. Currently, new wireless headsets that meet consumer criteria for wearability, price, portability and ease-of-use are coming to the market. It makes possible to spread the technology to applications in emotion recognition in many other areas such as entertainment, e-learning, virtual worlds, cyberworlds, etc. Automatic emotion recognition from EEG signals is receiving more attention with development of new forms of human-centric and human-driven interaction with digital media. In this paper, we concentrate on recognition of "inner" emotion from EEG signals as humans could control their facial expressions or vocal intonation.

There are different emotion classifications proposed by researchers. We follow two-dimensional Arousal-Valence model [7]. This model allows mapping discrete emotion labels in the Arousal-Valence coordinate system. One of emotion definitions is as follows: "The bodily changes follow directly the perception of the exciting fact, and that our feeling of the changes as they occur is the emotion" [8]. Our hypothesis is that the feeling of changes can be noticed from EEG as fractal dimension changes. We focused on study of fractal dimension model and algorithms, and developed one fractal based approach to emotion recognition.

To evoke emotions, different stimuli could be used: visual, auditory, and combined. They activate different areas of the brain. Our hypothesis is that emotions have spatio-temporal location. There is no easily available benchmark database of EEG labeled with emotions. But there are labeled databases of audio stimuli for emotion induction - International Affective Digitized Sounds (IADS) [9] and visual stimuli - International Affective Picture System (IAPS) [10]. Thus, we proposed and carried one experiment on emotion induction using IADS database of labeled audio stimuli. We also proposed and implemented an experiment with music stimuli to induce emotions by playing music pieces and prepared questionnaire for the participants to label the recorded EEG with corresponding emotions.

There are a number of algorithms for recognizing emotions. The main problem of such algorithms is a lack of accuracy. Research is needed to be carried out to evaluate different algorithms and propose algorithms with an improved accuracy. As emotion recognition is a new area, a benchmark database of EEG signals for different emotions is needed to be set up, which could be used for further research on EEG-based emotion recognition. Until now, only limited types of emotions could be recognized. Research could be done on more types of emotions recognition. Additionally, most of the emotion recognition algorithms were developed for off-line data processing. In our paper, we target real-time applications in 3D virtual environment. The user emotions are recognized and visualized in real time on his/her avatar. We add one more so-called "emotion dimension" to human computer interfaces. Although in this paper, we describe a standalone implementation of emotion recognition and visualization, it could be easily extended for further use in collaborative environments/cyberworlds.

In Section II A, review on emotion classification is given. In Section II B, emotion recognition algorithms from EEG are reviewed. In Section II C, a fractal dimension algorithm proposed by Higuchi is described. Our approach, emotion induction experiments, a novel fractal-based emotion recognition algorithm, data analysis and results are given in

Section III. Real-time emotion recognition and visualization of human emotions on 3D avatar using Haptek system [11] is discussed in Section IV. In Section V, conclusion and future work are given.

II. Related Works

A. Emotion Classification

There are different emotion classification systems. The taxonomy can be seen from two perspectives, dimensional and discrete one [12]. Plutchik defines eight basic emotion states: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. All other emotions can be formed by these basic ones, for example, disappointment is composed of surprise and sadness [13].

From the dimensional perspective, the most widely used one is the bipolar model where arousal and valence dimensions are considered. This emotion classification approach is advocated by Russell [7]. Here, the arousal dimension ranges from not aroused to excited, and the valence dimension ranges from negative to positive. The dimensional model is preferable in emotion recognition experiments due to the following advantage: dimensional model can locate discrete emotions in its space, even when no particular label can be used to define a certain feeling [12] [14].

B. Emotion Recognition Algorithms

There are an increasing number of researches done on EEG-based emotion recognition algorithms. In work [1], short-time Fourier Transform was used for feature extraction and Support Vector Machine (SVM) approach was employed to classify the data into different emotion modes. The result was 82.37% accuracy to distinguish the feeling of joy, sadness, anger and pleasure. A performance rate of 92.3% was obtained in [2] using Binary Linear Fisher's Discriminant Analysis and emotion states among positive/arousal, positive/calm, negative/calm and negative/arousal were differed. SVM was applied in work [3] for emotion classification with the accuracy for valence and arousal identification as 32% and 37% respectively. By applying lifting based wavelet transforms to extract features and Fuzzy C-Means clustering to do classification, sadness, happiness, disgust, and fear were recognized in work [4]. In work [5], optimization such as different window sizes, band-pass filters, normalization approaches and dimensionality reduction methods were investigated, and it achieved an increase in accuracy from 36.3% to 62.07% by SVM after applying these optimizations. Three emotion states: pleasant, neutral, and unpleasant were distinguished. By using Relevant Vector Machine, differentiation between happy and relaxed, relaxed and sad, happy and sad with a performance rate around 90% was obtained in work [6].

Although some researches achieved relatively high accuracy of emotion recognition, the proposed algorithms, were used only off-line. The number of electrodes used in emotion recognition is another problem, since the equipment with more electrodes is more expensive and it needs more time to set up the experiment.

Additionally, as the brain is a complicated system, the EEG signal is nonlinear and chaotic [15-16]. However, little has been done to investigate chaos of brain for emotion recognition. Works [1-6] were based on linear analysis, however, linear analysis such as Fourier Transform only preserves the power spectrum in the signal, but destroys the spike-wave structure [17].

A fractal dimension analysis is suitable for analyzing nonlinear systems and could be used in real-time EEG signal processing [18]. Early work such as [19] showed that fractal dimension could reflect the change of EEG signal; [20] showed that fractal dimension varied for different mental tasks; a more recent work like [15] revealed that when brain processed tasks which were of emotional difference only, fractal dimension can be used to differ these tasks. Work [21-22] used music as stimuli to elicit emotions, and applied fractal dimension for the analysis of the EEG signal. All these works show that fractal dimension is a potentially promising approach to investigate EEG-based emotion recognition. In our research, fractal dimension model is investigated to provide better accuracy and performance in EEG-based emotion recognition.

C. Fractal Dimension Model

In fractal analysis, fractal dimension (FD) values of geometric objects could reveal geometric complexity. For calculation of fractal dimension value, we implemented and analyzed two well-known algorithms Box-counting [23] and Higuchi [24]. Both of them were evaluated using Brownian and Weierstrass functions where "true value" is known [25]. Higuchi algorithm gave a better accuracy as it was closer to the theoretical FD values [26].

Let us describe the Higuchi algorithm as we apply it for FD calculation in our proposed fractal-based emotion recognition algorithm shown in Section III.

Let $X(1), X(2), ..., X(N)$ be a finite set of time series samples, the new time series is constructed as follows:

$$X_k^m : X(m), X(m+k), X(m+2k), ..., X(m+\left[\frac{N-m}{k}\right]\cdot k) \quad (1)$$

where $m = 1, 2, ..., k$, m is the initial time and k is the interval time.

Then, k sets of $L_m(k)$ are calculated as follows:

$$L_m(k) = \frac{\left\{\left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left|X\left(m+ik\right) - X\left(m+\left(i-1\right)\cdot k\right)\right|\right)\frac{N-1}{\left[\frac{N-m}{k}\right]\cdot k}\right\}}{k} \quad (2)$$

$\langle L(k)\rangle$ denotes the average value over k sets of $L_m(k)$ and the relationship exists as follows:

$$\langle L(k)\rangle \propto k^{-D} \quad (3)$$

Finally, the fractal dimension can be obtained by logarithmic plotting between different k and its associated $\langle L(k) \rangle$ [24].

III. Fractal Dimension Based Approach to Emotion Recognition

In this paper, we proposed a fractal dimension based approach to EEG-based emotion recognition. First, we designed and implemented emotion induction experiments using two-dimensional model to describe emotions. Then, we analyzed EEG recordings with Higuchi algorithm and our proposed algorithm for online emotion recognition.

A. Emotion Induction Experiments

As we mentioned in Introduction, there is no easily available benchmark database of EEG recordings with labeled emotions. We designed two experiments to elicit emotions with audio stimuli. Five truncated songs which lasted for 1 minute each were used in experiment 1, and the target emotions were negative/low aroused (sad), positive/low aroused (pleasant), negative/high aroused (fear), positive/high aroused (happy) and negative/high aroused (angry). Sound clips selected from the International Affective Digitized Sounds (IADS) were used in experiment 2. All the sounds in the IADS database are labeled with their arousal and valence values. 27 clips were chosen to induce five emotional states: 3 clips for neutral with mean arousal ratings ranging between 4.79 and 5.15, mean valence rating ranging from 4.83 to 5.09; 6 clips for each of positive/low aroused, positive/high aroused, negative/low aroused and negative/high aroused emotions with mean arousal rating ranging between 3.36 and 4.47; 6.62 and 7.15; 3.51 and 4.75; 7.94 and 8.35 respectively, and mean valence rating ranging between 6.62 and 7.51; 7.17 and 7.90; 4.01 and 4.72; 1.36 and 1.76 respectively.

10 participants, 2 female and 8 male students whose ages ranged from 23 to 35, participated in the first music experiment.

12 subjects, 3 female students and 9 male students whose ages ranged from 22 to 35, participated in the second IADS experiment. None of the subjects had history of mental illness.

After a participant was invited to the project room, he or she was briefly introduced to the experiment protocol and the use of self-assessment questionnaire. Then, the participant was seated in front of the computer which played the audio stimuli. He or she was required to keep still and eyes closed during experiment sessions to avoid muscle movement and eye blinking artifacts.

Experiment 1 was consisted from five sessions. Each session targeted one type of emotion induction. There was a 60 seconds silent period at the beginning of each session. After that, one piece of music truncated to 1 minute duration was played to the subject.

For experiment 2 using stimuli from IADS, 5 sessions, namely: session 1 - neutral, session 2 - positive/low aroused, session 3 - positive/high aroused, session 4 - negative/low aroused, session 5 - negative/high aroused were prepared. In each session, there was a 6 seconds' silent break, then 6 clips of IADS stimuli aiming at one particular emotion were played to the subjects. For neutral state, since only three sounds clips were available, each clip was played twice in order to keep the same session duration.

For both experiments, the subjects needed to complete the questionnaire after listening to music/sounds. In the questionnaire, the Self-Assessment Manikin (SAM) technique [27] with two dimensions: arousal and valence and five levels indicating the intensity of both dimensions, was employed for emotion state measurement. Additionally, the subjects were asked to write down their feelings in a few words.

Emotiv device [28] and Pet 2 [29] were considered for carrying out experiments. Finally, Emotiv device with 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 following the American Electroencephalographic Society Standard [30] was used in the experiments. The sampling rate is 128Hz.

B. Data Analysis and Results

The data collected in our two experiments using the Emotiv headset was analyzed to find spatio-temporal emotion patterns of high and low arousal level with positive and negative valence level. 2 to 42 Hz band-pass filter was applied to the raw data as the major EEG waves (alpha, theta, beta, delta, and gamma) lie in this band [31-32]. Then, Higuchi fractal dimension algorithm described in section II C was applied for FD values calculations. We implemented the algorithm with a sliding window where the window size was 1024 samples and 99% overlapping was applied to calculate FD values of the filtered data.

In the first experiment using music stimuli, the data from 13th to 24th seconds of recording was processed. In the second experiment using IADS clips, the data from 2nd to the 13th seconds of recording was processed.

The arousal level could be identified from different electrode locations. FC6 was selected for the arousal level recognition as the FD values computed from it gave better arousal difference compared to other channels. The mean of FD values computed from FC6 aiming at recognizing the arousal level for all subjects in music and IADS experiments is shown in Table I and Table II. Two FD values for high arousal level with negative and positive valence, and two FD values for low arousal level with negative and positive valence are presented in the Tables as follows: negative high aroused (N/HA), positive high aroused (P/HA), negative low aroused (N/LA), and positive low aroused (P/LA). In Table I, it is shown that 10 subjects participated in the Music experiment. In Table II, it is shown that 12 subjects participated in IADS experiment. Based on the self-assessment questionnaires, 46 pairs of comparisons from different subjects between high aroused and low aroused states regardless of the valence level were used. 39/46 (84.9%) showed that the higher arousal was associated with the larger FD values. This phenomenon is illustrated in Table I and II as the mean of FD values for the high aroused states (N/HA and P/HA) is larger than the low aroused states (N/LA and P/LA). For example, for the subject #1 N/HA value 1.9028 is larger than N/LA value 1.7647 and P/LA value 1.8592, and P/HA value 1.9015 is larger than N/LA value 1.7647 and P/LA value 1.8592. In Table I and II, we denoted the FD value as X if the subject's feeling was different from the targeting emotion by self-assessment questioner report. Thus, we eliminated such cases from our analysis.

TABLE I. FD VALUES FOR AROUSAL LEVEL ANALYSIS OF MUSIC EXPERIMENT

Music	Emotion State FD Value			
	N/HA	***P/HA***	***N/LA***	***P/LA***
Subject #1	1.9028	1.9015	1.7647	1.8592
Subject #2	X	1.9274	X	1.9268
Subject #3	1.9104	1.9274	1.7579	1.8426
Subject #4	1.9842	1.956	1.8755	1.9361
Subject #5	1.7909	1.8351	1.8242	X
Subject #6	1.9111	X	X	1.9127
Subject #7	1.9352	1.9231	1.9106	1.9204
Subject #8	X	X	X	X
Subject #9	1.9253	1.939	X	1.9203
Subject #10	1.8507	1.8842	X	1.8798

a. "X" denotes the data was not used according to self-report

TABLE II. FD VALUES FOR AROUSAL LEVEL ANALYSIS OF IADS EXPERIMENT

IADS	Emotion State FD Value			
	N/HA	***P/HA***	***N/LA***	***P/LA***
Subject #1	1.8878	1.8478	X	1.8042
Subject #2	1.9599	1.922	1.938	1.8237
Subject #3	1.9418	1.9507	1.9201	X
Subject #4	1.9215	1.917	1.9265	1.9118
Subject #5	1.7215	1.9271	X	1.8659
Subject #6	1.8898	1.8902	1.888	X
Subject #7	X	X	X	X
Subject #8	X	X	X	X
Subject #9	1.9261	1.9241	1.7437	X
Subject #10	1.9223	1.9333	X	1.9026
Subject #11	1.8796	1.8543	1.7183	X
Subject #12	X	X	X	X

a. "X" denotes the data was not used according to self-report

Frontal brain area plays an important role in the reflection of the valence level. In works [33-34], it shows that there is frontal lateralization for positive and negative emotions. Generally, right hemisphere is more active during negative emotion, and left hemisphere is more active during positive emotion. However, there are also studies such as works [35-36] oppose this hypothesis.

In our study, the difference between FD values from electrode pair AF3 (left hemisphere) and F4 (right hemisphere) were used to identify valence level and test the lateralization theory.

For valence level, the difference between FD values (AF3-F4) was processed for each subject. It was found that more stable pattern can be achieved by differentiating valence level within the same arousal level, either high aroused or low aroused. The results revealed partial support for the asymmetric frontal hypothesis. Although not all the subjects' dominant hemisphere for positive and negative emotion was the same as expected in the asymmetric hypothesis, the pattern of lateralization for a particular subject was consistent among different experiments with similar arousal level. 10 subjects' data was available for comparison of positive and negative emotion states with similar arousal level. 9/10 (90%) has shown the consistent pattern as follows. For example, subject's EEG data showed the larger difference between AF3 and F4 values for negative emotions than for positive emotions in all experiment trails with different valence levels but similar arousal levels. Five subjects have the larger difference AF3-F4 value during the experience of negative emotion, while 4 subjects have larger AF3-F4 value when having positive emotions. This phenomenon may indicate that the frontal lateralization exists with individual differences, and it may not be applicable for everyone that the left hemisphere is more active for positive and right hemisphere is more active for negative emotions. It could be opposite for some individuals, and this outcome complies with the conclusion made in work [37] that individual difference may affect the processing of emotion by brain.

Based on the result of our analysis, we developed the following real-time emotion recognition algorithm described in the next section.

C. *Real-Time Emotion Recognition Algorithm*

As it was mentioned in Introduction, we follow two-dimensional model Arousal-Valence described in section II A. This model allows the mapping of the discrete emotion labels in the Arousal-Valence coordinate system as shown in Fig. 1.

The advantage of using this model is that we can define arousal and valence levels of emotions with the calculated FD values. For example, the increase in arousal level corresponds to increase of FD values. Then, by using ranges of arousal and valence level, we could obtain discrete emotions from the model. Finally, any emotion that can be represented in the Arousal-Valence model can be recognized by our emotion recognition algorithm.

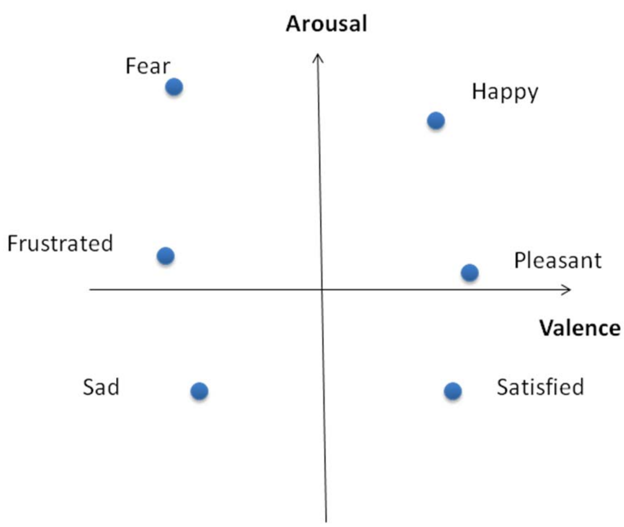

Figure 1. Emotion labels in arousal-valence dimension (Adapted from Russell's circumplex model [38]).

The emotion recognition algorithm for real time is illustrated in Fig. 2. The raw EEG data gathered from AF3, F4 and FC6 are the input to the 2 to 42 Hz band-pass filter. Then, Higuchi fractal dimension algorithm with a sliding window of window size 1024 and 99% overlapping is applied to the filtered data. The benefit of the usage of the sliding window is that it enables real time processing.

The FD value calculated from FC6 is used to distinguish the arousal level independently by comparing with default threshold extracted from our experiments' results described in section III B. As shown in Fig. 1, the change of FD could be mapped along the arousal axis since our experiments revealed that higher arousal level was associated with larger FD values. Based on this observation, continuous recognition of changing emotion from low arousal to high arousal is enabled.

The difference of FD values between left hemisphere and right hemisphere (AF3-F4) is computed simultaneously. After the arousal level has been identified, the valence level of emotions is recognized within the similar arousal level by comparing the difference of FD with another threshold which was set for valence level recognition.

Finally based on the arousal level and valence level, the emotions are mapped into 2D model.

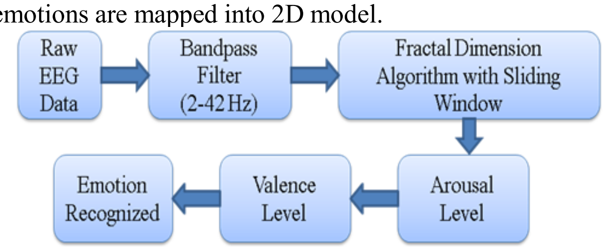

Figure 2. The emotion recognition algorithm overview.

In the algorithm, we set default thresholds for real time emotion recognition based on the experiments' results. However, because of the existence of individual difference which means the pattern of emotion for one particular subject is consistent, but FD values may vary among different subjects, training session needs to be introduced in order to improve the accuracy.

The training session scheme is illustrated in Fig. 3. The procedure is similar with the real time scheme, except the input is EEG data of anticipated emotion. Thresholds are set and the lateralization pattern is found out based on the data collected from the training session for the user.

When the subject wants to use this system after training, the procedure is illustrated as the lower part below the dash line in Fig. 3. The pattern of newly collected EEG data is recognized based on comparison with the training session, and the emotion state is classified.

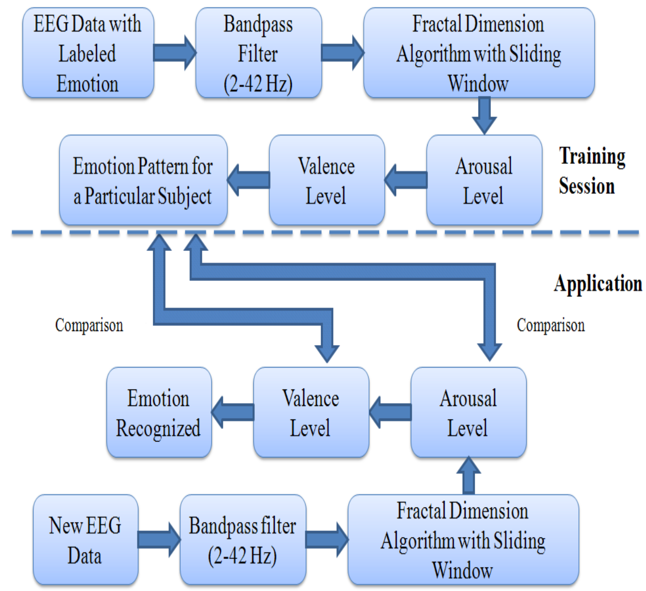

Figure 3. An emotion recognition scheme with training session.

IV. Real Time Application

In order to visualize the recognized emotions, we implemented our algorithm with Haptek activex control system [11]. Microsoft Visual C++ 2008 was used in this project.

Haptek software is a 3D model with predefined parameters for controlling facial muscles visualization, thereby enables users to create customized emotions and expressions. Haptek supports stand-alone and web-based application.

A. *Data Acquisition*

EEG data is acquired using Emotiv headset at 128 Hz. We used Emotiv Software Development Kit for acquiring raw data from the device. Three out of fourteen Emotiv's channels at locations AF3, F4 and FC6 are fed into the algorithm for the emotion recognition process.

B. *Data Processing*

A data stream from the Emotiv device is stored in a buffer. Every time a read command is triggered, all the samples in the buffer are taken out and the buffer is cleared.

Therefore, the number of data obtainable at a time depends on how long the samples have accumulated in the buffer.

The fractal algorithm requires data to be fed in a bunch of 1024 samples at a time for one channel. Therefore, we use a queue to buffer the data from Emotiv's buffer to the algorithm. The queue is refreshed by the current number of samples in Emotiv's buffer every time the read command is triggered as shown in Fig. 4. In the algorithm, those obsolete values in the queue are replaced by latest values in the Emotiv buffer at the time.

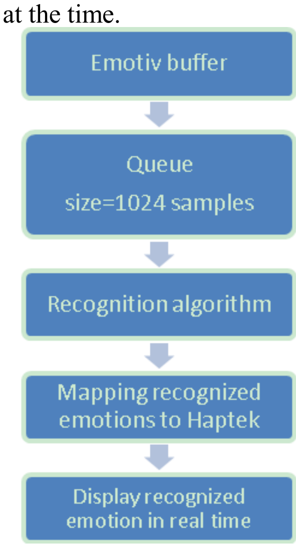

Figure 4. An illustration of the implementation process of the application.

C. *Emotion Mapping to Haptex*

Haptek Activex control provides functions and commands to change facial expressions of 3D avatars. We used an avatar available with free version of Haptek development package for this application. We defined six emotions by changing the parameters controlling the facial muscles of the Haptek emotion avatar. Those emotions are: fear, frustrated, sad, happy, pleasant and satisfied. The above emotions can be recognized by the proposed emotion recognition algorithm described in the section III.

For the mapping, arousal and valence levels are transformed into discrete values using thresholds. After this step, arousal level can only take one of the following values 0, 1 or 2 and valence 0 or 1 as shown in Fig. 5. Combination of discrete values of arousal and valence level gives six types of emotions.

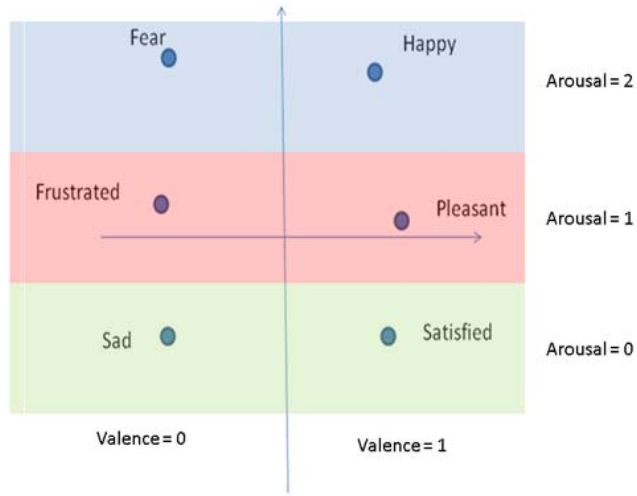

Figure 5. Illustration of discrete arousal and valence levels.

Mapping of discrete values of (Arousal level, Valence level) into 6 emotions is shown in Table III.

TABLE III. MAPPING OF COMBINATIONS OF (VALENCE, AROUSAL) AND CORRESPONDING EMOTIONS

(Valence, Arousal)	Emotion
(0,0)	Sad
(0,1)	Frustrated
(0,2)	Fear
(1,0)	Satisfied
(1,1)	Pleasant
(1,2)	Happy

Picture of the user with headset and pictures of six emotions created using Haptek are shown in Fig. 6 and Fig. 7 respectively.

Figure 6. User with Emotiv headset.

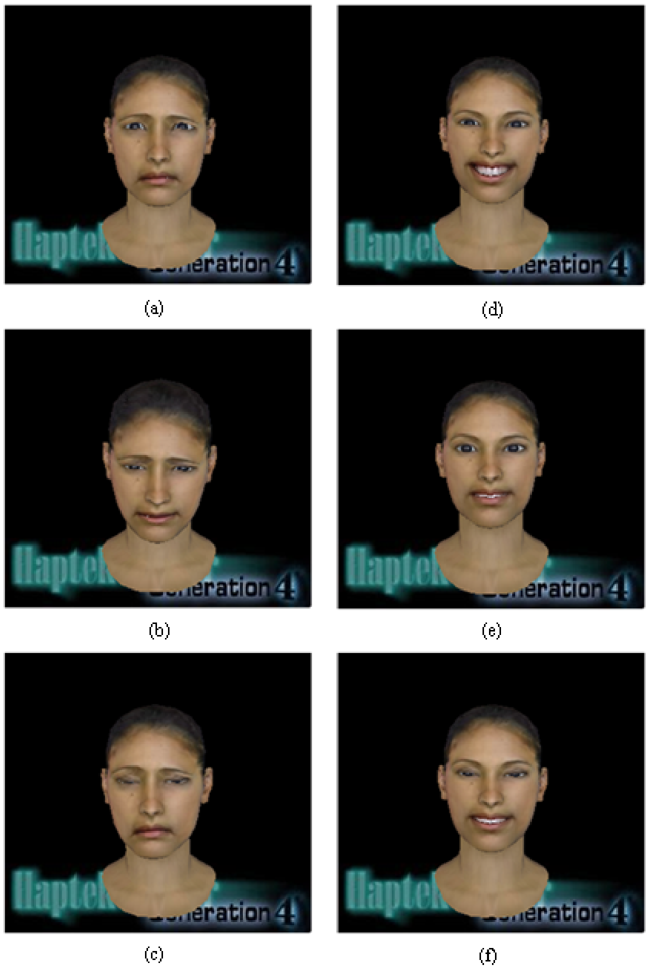

Figure 7. Six visualized emotions with Haptek (a) Fear (b) Frustrated (c) Sad (d) Happy (e) Pleasant (f) Satisfied.

V. Conclusion and Future Work

In this paper, emotion classifications, emotion recognition algorithms, and emotion evoking experiments are reviewed. We proposed and implemented a novel fractal dimension based algorithm for recognition of emotions from EEG in real time. We implemented our algorithm with free downloaded system Haptek that is also commercially available. The system allows visualization of emotions as facial expressions of avatars in 3D collaborative environments in real time.

Compared with other works, our algorithm uses fewer electrodes. We recognized emotions with AF3, F4 and FC6 electrodes, however, for example, in works [4] and [5], 63 and 16 electrodes were used respectively. Until now, to our best knowledge there is no real-time EEG-based emotion recognition algorithms reported. We implemented a novel real-time emotion recognition algorithm based on fractal dimension calculation. In this paper, we implemented recognition of six emotions: fear, frustrated, sad, happy, pleasant and satisfied. However, our approach based on FD calculation allows recognize any emotion that can be defined in 2 dimensional Arousal-Valence model.

Currently, real-time emotion recognition and visualization is implemented as a standalone application. The next step of the project is an integration of our tools in Co-Spaces on the Web targeting an entertainment industry.

A short video about the emotion recognition algorithm implemented in real time with the Haptex system is presented at http://www3.ntu.edu.sg/home/EOSourina/.

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