A REAL-TIME FRACTAL-BASED BRAIN STATE RECOGNITION FROM EEG AND ITS APPLICATIONS

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Keywords: BCI, Neurofeedback, Emotion recognition, Fractal dimension, EEG, Real-time applications.

Abstract: EEG-based immersion is a new direction in research and development on human computer interfaces. It has attracted recently more attention from the research community and industry as wireless EEG reading devices became easily available on the market. EEG-based technology has been applied in anaesthesiology, psychology, serious games or even in marketing. As EEG signal is considered to have a fractal nature, we proposed and developed a novel spatio-temporal fractal based approach to the brain state quantification. The real-time algorithms of emotion recognition and concentration level recognition were implemented and integrated in human-computer interfaces of EEG-enable applications. In this paper, EEG-based "serious" games for concentration training and emotion-enable applications including emotion-based music therapy on the Web were proposed and implemented.

1 INTRODUCTION

Immersive human interaction with computer systems should use all human senses such as visual, audio, tactile, odour, taste, etc to make virtual or even non-virtual experience more real. In the case of human computer systems, human receives information from the system using eyes, ears, skin, nose, etc and the information is processed by the corresponding lobes of the brain. Then, the user enters information into the computer system using the implemented human-computer interface system scenarios. To make the human-computer interfaces more seamlessness the information could be entered involuntary as well. It could be entered into the computer by cameras, sensors based tracking systems, and by biofeedback sensors. Then, the information could be processed by the corresponding algorithms depending on the system application. In this paper, we study a novel dimension of human-computer interfaces that is based on real-time EEG recordings and its recognition. Electroencephalogram (EEG) is a non-invasive technique recording the electrical potential over the scalp which is produced by the activities of brain cortex, and reflects the state of the brain (Nunez and Srinivasan, 2006). EEG technique gives us an easy and portable way to monitor brain activities by using suitable signal processing and classification methods and algorithms.

We proposed new algorithms of brain state recognition including emotion recognition and concentration level recognition, and innovative integrated methods and tools for implementation of the EEG-based user immersion and interaction. Algorithms of the "inner" brain state quantification including emotion recognition would advance research on human computer interaction bringing up the proposed novel objective quantification methods and algorithms as new research tools in medical applications, entertainment, and even novel digital art methodology applications, and allowing us an integration of the brain state quantification algorithms in the human computer interfaces. It would lead to the implementation of the applications such as EEG-based serious games including neurofeedback games, emotion-enable personalized search on the Web, experimental art animation, personalized avatars seamlessness communicating with virtual objects, other avatars, or even social robots working with elderly people, etc.

In this paper, we describe a novel spatio-temporal fractal-based approach to brain state recognition particularly to recognition of the concentration levels and emotion recognition. The method is general, and it could be used as a basis for the development of other brain states recognition

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algorithms as well. Our approach consists from two parts: interactive tools allowing dynamic analysis of EEG signals amplitudes and other parameters distribution over the brain lobes, and fractal dimension algorithms with sliding window that can estimate complexity of the signal by calculating fractal dimensions values changing over time. The algorithms of concentration level recognition and emotion recognition use just one fractal feature per channel that allows us to implement real-time EEG-enable applications. We implemented real-time applications such as blobby 3D mapping, concentration games, emotion-enable search on the Web, etc. that are described in this paper.

In Section 2.1, we describe Brain Computer Interfaces (BCI) and neurofeedback techniques. In Section 2.2, emotion recognition algorithms are reviewed. Then, we describe the proposed spatio-temporal fractal-based approach to the brain state recognition. In Section 3.1, 3D Mapping of EEG signal with blobby model is presented. In Section 3.2, fractal dimension algorithms applied for extraction of fractal dimension features of EEG signal with sliding window are elaborated. An implementation of the overall algorithm is given in Section 4. Real-time EEG-enable applications including EEG-based serious games and emotion-based music search are described in Section 5.

2 RELATED WORK

2.1 BCI and Neurofeedback

Brain Computer Interfaces (BCIs) are the systems that use brain signals to create a new channel of interaction of humans with computers or other devices. Mostly the systems are used for disabled or elderly persons. Recently, efforts have been made on the development of EEG-based real-time applications in multimedia communication, rehabilitation games, interaction in virtual environments, etc. Traditionally, neurofeedback is a technique that allows the user voluntary change his/her brain state based on the visual or audio feedback from the system corresponding to the recognized from the user EEG state of the brain. The user by doing some exercises recommended by the doctor or just by playing the serious game with neurofeedback learns how to improve his/her brain plasticity. Neurofeedback could recover some psychological disorders or just help to improve some skills of concentration, meditation, etc. Some research demonstrates that both the EEG and Event Related Potential (ERP) distortion can reflect psychological disorders such as Attention Deficit Hyperactivity Disorder (ADHD) (Lubar et al., 1995, Fuchs et al., 2003), Autistic Spectrum Disorders (ASD) (Coben et al., 2010, Kouijzer et al., 2010), Substance Use Disorders (SUD) including alcoholics and drug abuse (Saxby and Peniston, 1995, Sokhadze et al., 2008), etc. Neurofeedback can be used for treating these disorders besides medical treatments. Many neurofeedback games were assessed, and it was proved that they have a healing effect on patients with ADHD while the patient has abnormal θ/β ratio of EEG. Besides the ratio, the distortion in Slow Cortical Potential (SCP) was also notified in (Gevensleben et al., 2009). Both the frequency band neurofeedback training and the SCP neurofeedback training could achieve a good healing effect for ADHD (Gevensleben et al., 2009). Two EEG signal processing methods are prevalent in BCI systems: power spectrum analysis for different frequency bands and event related potential analysis. As the different frequency band reflects different brain functions (Demos, 2005), frequency training is a well-known technique applied in clinic applications together with the Quantitative EEG (QEEG) protocol. In QEEG protocol, the power over different bands is assessed from the patients EEG signals, and compared to the reference QEEG database. Pathology and the corresponding recovery protocol can be generated with the statistical model. The ERP analysis including SCP and P300 analysis is a technique to analyze the event synchronized EEG potential. SCP has shown its usability in ADHD treatment in (Gevensleben et al., 2009), and P300 component training could be used for drug abuse rehabilitation (Sokhadze et al., 2008).

Although an efficiency of EEG linear features application were proved in clinical treatments, the nonlinear methods, e.g. entropy analysis and fractal dimension analysis, became popular in EEG processing due to the nonlinearity of the EEG signals. The hypothesis is that a non-linear fractal dimension approach allows quantify brain states corresponding to the concentration levels, pain levels, etc. In work (Wang et al., 2010b, Wang et al., 2010a), two well-known algorithms such as Box-counting (Block et al., 1990) and Higuchi (Higuchi, 1988) were applied in concentration level recognition in neurofeedback games, and the efficiency was approved.

2.2 Emotion Recognition Algorithms

Emotion recognition from EEG could reveal the "inner" feeling of the user, and then, it could be used in a therapy or to create an emotion-enable avatar of the user or other real-time applications. Emotion recognition algorithms consist from two parts: feature extraction and classification. For real-time applications, an objective is to develop fast algorithms recognizing more emotions with fewer electrodes used. Currently, mostly off-line recognition algorithms were proposed which are shown in the Table 1. EEG-based emotion recognition algorithms could be divided into two groups: a subject-dependent and a subject-independent one. In the Table 1, the algorithms are compared by feature extraction and classification algorithms used, by emotion types recognized and by the algorithms accuracy. The algorithms are also differed by the number of the electrodes used in the emotion recognition. In the Table 1, in works (Ishino and Hagiwara, 2003, Zhang and Lee, 2009, Takahashi, 2004, Petrantonakis and Hadjileontiadis, 2010) 3 or 2 electrodes were used. All other works employed more than 32 electrodes to collect EEG data.

In (Liu et al., 2010), we proposed real-time algorithm only using 3 channels in total. Fractal dimension algorithms were applied to compute fractal based features, and a real time EEG-based emotion recognition algorithm was implemented with predefined thresholds based on the training session analysis. In our work, by recognizing arousal and valence level with an accuracy of 84.9% and 90% respectively, the satisfied, pleasant, happy, frustrated, sad, fear, and neutral emotions were differentiated. Since the discrete emotions can be mapped to the 2D emotion model, and fractal dimension values can be mapped to 2D emotion model as well, more emotions that are defined in 2D model could be distinguished.

Table 1: Off-line emotion recognition algorithms.

Author	Feature and Classification	Emotion	Result
Subject-dependent emotion recognition works			
(Ishino and Hagiwara, 2003)	**Feature** FFT; Wavelet transform; Variance, mean **Classification** Neural Network	Joy, sad, angry, relaxed	Joy: 54.5% Anger: 67.7% Sorrow: 59% Relaxati-on: 62.9%
(Zhang and Lee, 2009)	**Feature** PCA **Classification** Linear Kernel SVM; RBF Kernel SVM	Negative and positive	73.00%
(Chanel et al., 2006)	**Feature** 6 frequency bands from different locations **Classification** Naïve Bayes; Fisher Discriminant Analysis	3 degree of arousal	58%
(Chanel et al., 2009)	**Feature** Short Time Fourier Transform; Mutual Information **Classification** Discriminant Analysis; SVM; Relevance Vector Machine	Positive/ arousal, neutral/ calm, negative/ arousal	63%
(Lin et al., 2009)	**Feature:** ASM 12 **Classification** SVM	Joy, anger, sadness, pleasure	90.72%
Subject-independent emotion recognition works			
(Khalili and Moradi, 2009)	**Feature** Statistical feature combined with Correlation dimension **Classification** Quadratic Discriminant Analysis	Calm, positive aroused, negative aroused	76.66%
(Takahashi, 2004)	**Feature** statistical features **Classification** SVM, Neural Networks	Joy, anger, sadness, fear and realizati-on	41.7% for five emotions, 66.7% for three emotions
(Petrantonakis and Hadjileontiadis, 2010)	**Feature:** Statistical features, wavelet based features, higher order crossings. **Classification:** SVM, QDA, KNN, Mahalanobis Distance	Happy, surprised, angry, fear, disgust, sad	62.3% for single channel case, 83.33% for combined channel case

3 SPATIO-TEMPORAL APPROACH

The spatio-temporal approach combines two methods: a spatio-temporal analysis and fractal based analysis. The spatio-temporal analysis includes real-time 3D mapping of EEG signal amplitude or other parameters, for example, fractal dimension values, with blobby model defined by implicit functions and applying set-theoretic operations over the moving shapes to isolate activities common for the signal during the time interval, as well as those that are unique one. The proposed fractal based method allows us to estimate the signal complexity changing over time and then, recognize the brain state.

3.1 3D Mapping of EEG

We proposed a novel method of EEG analysis based on 3D mapping of EEG data. We employed a concept of a dynamic 3D volumetric "blobby" shape to visualize the EEG signal changes over time. The blobby-like objects were firstly introduced in (Blinn, 1982, Wyvill et al., 1986). A time-dependent "blobby" object is defined using implicit functions that allow us to propose and implement set-theoretic operations over the time changing shapes for further analysis.

This object is defined using so-called FRep representation proposed in (Pasko et al., 1995) and extended to spatio-temporal model in (Kulish et al., 2006a, Sourina et al., 2009) where it was described by the following formula:

$$\frac{f(x,y,z,t)=\sum_{i=1}^{M}a_i e^{-r_i.b_i(t)}-g\geq 0}{r_i=\sqrt{(x-x_i)^2+(y-y_i)^2+(z-z_i)^2}} \tag{1}$$

where a is a scale factor, b is an exponent scale factor changing over time, g is a threshold value, and m is the number of electrodes used.

At any given point (x, y, z, t), function f can take negative, positive or zero values. The point is considered on the surface of the object if the function value is zero, inside the object if the function value is positive, and outside the object otherwise. The shape changes through time due to the variable values of the exponent factor b according to the signal. Its size and appearance visually reflect the brain activity. For a better visual impression, the blobby shape is superimposed on a 3D head model. Besides just a visual comparison, we proposed to apply set-theoretic ("Boolean") operations to the moving shapes to isolate activities common for both of them per time point, as well as those that are unique for either one. Furthermore, the group set-theoretic operations applied to the individual time frames of the moving shape allow us to isolate idle parts of the brain as well as to estimate an average level of the brain activity. The proposed operations could be applied over one or/and over two datasets. On one data set, we can do intersection of all shapes to show constant activity on the time interval, and union of all shapes to show the overall maximum activity. On two data sets, we could apply an intersection to show common activity, union to show overall maximum activity and subtraction to show activities which are characteristic to one set.

3.2 Fractal-based Approach

Fractal dimension (FD) is a measurement of complexity and irregularity of the object based on an entropy analysis. Entropy is a measure of the disorder in physical systems, or an amount of information that may be gained by observations of the disordered systems. A common practice to distinguish among possible classes of time series is to determine their so-called correlation dimension. The correlation dimension, however, belongs to an infinite family of fractal dimensions (Hentschel and Procaccia, 1983). Hence, there is a hope that the use of the whole family of fractal dimensions may be advantageous in comparison to using only some of these dimensions. The concept of generalized entropy of a probability distribution was introduced by Alfred Renyi (Renyi, 1955). Based on the moments of order q of the probability p_i, Renyi obtained the following expression for entropy

$$S_q=\frac{1}{q-1}\log\sum_{i=1}^{N}p_i^q \tag{2}$$

where q is not necessarily an integer and log denotes $\log_2$. Note that for $q\to 1$, Eq. (2) yields the well-known entropy of a discrete probability distribution (Shannon, 1998):

$$S_1=-\sum_{i=1}^{N}p_i\log p_i \tag{3}$$

There are various methods to calculate fractal dimensions. In works (Kulish et al., 2006b, Kulish et al., 2006a), the generalized Renyi approach based on Renyi entropy and calculation of the whole spectra of fractal dimensions to quantify brain states were studied. In our real-time applications, we apply only Hausdorff dimension when $q=0$ in (2). We implemented two well-known Higuchi (Higuchi, 1988) and Box-counting (Block et al., 1990) algorithms calculating fractal dimension. Both of them were evaluated using mono-fractal Brownian and Weierstrass functions where theoretical FD values are known (Wang et al., 2010a). Higuchi algorithm gave a better accuracy as FD values were closer to the theoretical FD ones.

The algorithms were used in the proposed algorithm of FD feature extraction with sliding window for concentration level recognition and emotion level recognition.

The Box-counting and Higuchi algorithms are described as follows.

3.2.1 Box-counting Method

Fractal dimension D_B is defined in Box counting method (Block et al., 1990) as

$$D_B \simeq -\lim_{\varepsilon \to 0} \frac{\ln N(\varepsilon)}{\ln\left(\frac{1}{\varepsilon}\right)} \qquad (4)$$

Equivalently,

$$D_B = -\lim_{\varepsilon \to 0} \frac{\ln N(\varepsilon)}{\ln(\varepsilon)} \qquad (5)$$

where $N(\varepsilon)$ is the number of boxes of length ε which cover the whole data set.

Our implementation of the above box counting formula is based on (Phothisonothai and Nakagawa, 2007). A time series data are covered by a grid of boxes of length ε. $N(\varepsilon)$ is the number of boxes that the curve intersects with the grid. Different values of ε result in different number of boxes and hence different values of $N(\varepsilon)$. Therefore, the curve of $\ln N(\varepsilon)$ is plotted versus $\ln(\varepsilon)$ and D_B is calculated as the slope of that curve multiplied by -1.

3.2.2 Higuchi Method

The following implementation is based on work (Higuchi, 1988).

Suppose we want to calculate fractal dimension for a time series $x(1), x(2), \ldots, x(n)$

Step 1: Choose one value of k

Step 2: Construct the sub-series X_k^m from the time series as following

$$x(m), x(m+k), \ldots, x\left(m + \left[\frac{N-m}{k}\right].k\right) \qquad (6)$$

where $m = 1, 2, \ldots, k$ and [ ] denotes Gaussian notation which rounds a number in the brackets to its largest integer which is equal to or smaller than itself, m the initial time and k the time interval. For example, when $k = 3$ and $n = 100$ we have 3 sub-series as follows:

$$X_3^1 : x(1), x(4), x(7), \ldots, x(100)$$

$$X_3^2 : x(2), x(5), x(8), \ldots, x(98)$$

$$X_3^3 : x(3), x(6), x(9), \ldots, x(99)$$

Then, every length of each sub-series X_k^m is calculated. Length $L_m(k)$ of X_k^m is equal to

$$\frac{\left\{ \frac{\left(\sum_{i=1}^{\frac{N-m}{k}} \left| x(m+ik) - x(m+(i-1).k) \right| \right)(N-1)}{\left[\frac{N-m}{k}\right].k} \right\}}{k} \qquad (7)$$

Step 3: Calculate the average length $L(k)$ of all $L_m(k)$.

Step 4: Repeat step 1 to 3 for several values of k.

Step5: Slope of the curve of $\ln(L(k))$ versus $\ln(k)$ is approximated. Fractal dimension value is the slope multiplied by -1.

4 IMPLEMENTATION

The proposed real-time system diagram is shown in Figure 1. The user receives stimuli from the computer system such as visual, audio, etc. Then, the mental process of the user thinking is recognized from his/her EEG that is acquired by the EEG device. An overall recognition algorithm used in the real-time applications consists from the following steps: data sampling and pre-processing including data filtering, feature extraction, and subject-dependent machine learning algorithm. Then the command to the feedback system is formed based on the recognition results.

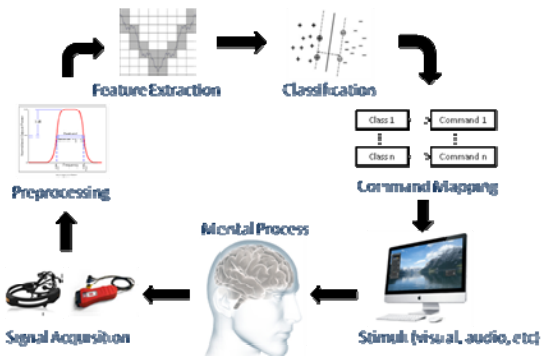


Figure 1: Diagram for non-invasive BCI system.

4.1 Pre-processing

The collected data are filtered by a 2-42 Hz bandpass filter since major waves of EEG lie in this band (Sanei and Chambers, 2007).

4.2 Features Extraction

The next step after the data pre-processing is feature extraction. We apply a sliding window and calculate one FD value per sample per channel. Number of channels used in the recognition algorithm defines a size of the feature vector as follows:

$$F = \{FD_1, FD_2, ...FD_m\} \tag{8}$$

where m is number of channels

In the concentration level recognition algorithm, we have one feature as only one channel is used (Wang et al., 2010a). In the emotion recognition algorithm, there are 3 features in the vector as 3 channels are used (Liu et al., 2010). Thus, in our approach we use one FD value per channel.

4.3 Classification Algorithms

Currently, we implemented a simple real-time subject-dependent classification algorithm based on threshold FD values that are calculated during a short training session. Note that off-line processing with SVM classifier of the EEG labelled with emotions and concentration levels gave us similar accuracy as the real time implementation algorithm used thresholds.

5 APPLICATIONS

EEG data are collected by Emotiv device with 14 electrodes located at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 standardized by the American Electroencephalographic Society (1991). The sampling rate is 128Hz. To be able to use any EEG device a program reading raw EEG signals is needed to be implemented. Currently, our applications could also work with Pet 2 and Mindset 24. All electrodes can be active in the system. The steps of an overall algorithm of the real-time application are as follows. First, raw data are read from the EEG device, filtered with band pass filter 2-42 Hz, and entered to the corresponding brain state recognition algorithm. Then, the results of the recognition are fed to the developed game, web site, or any other real-time software.

5.1 3D Mapping of EEG

We proposed a spatio-temporal approach to EEG analysis. 3D blobby-based EEG mapping was implemented for offline processing. To monitor and analyze the subject/user brain state in real time, a system "VisBrain" was implemented. Signal amplitude values are visualized with blobby model, color or "pins". In Figure 2, spatio-temporal visualization of EEG signals is shown with the 3D blobby mapping. The blobby model allows assessing a spatio-temporal pattern of the subject/user EEGs corresponding to different brain states.

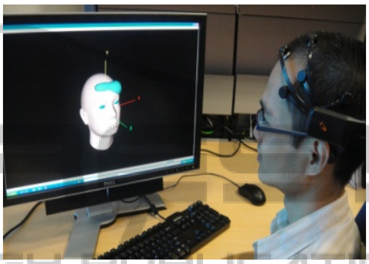


Figure 2: Real-time system "VisBrain" for spatio-temporal analysis.

5.2 EEG-based Serious Games

The EEG-based serious game design includes two parts: signal processing algorithms and a 2D/3D or virtual reality game part. Raw EEG signals collected by the device from the user brain are filtered and analyzed by signal processing algorithms, and the resulting values are interpreted in the game as an additional game control using just the "brain power". A therapeutic effect of such games consists from combination of a distraction effect of the game and an effect from the learning by the user/patient how to control the game by changing voluntary his/her brain state, for example, learning how to improve the user's concentration level. We developed two concentration games named "Brain Chi" and "Dancing Robot", and one game for stress management named "Pipe". They are simple single-player games implemented with the game engines SDL, Panda3D, and Adobe Flash CS4 correspondingly. The recognized relaxation/ concentration/ stress level values from EEG could be interpreted in the games as any visual/audio effects or even as a behaviour change of the game characters.

In the "Brain Chi" game, the relaxation/ concentration level of the user is associated with radius of a "growing/shrinking" ball. It allows the "little boy" character to fight enemies by "growing" the ball. In the "Dancing Robot" game, the relaxation/concentration level is associated with the "robot" character behaviour. When the concentration level of the user increases, the robot character starts to move faster. If the user is fully relaxed, the robot stops dancing. In our implementation, the concentration and relaxation levels could be easily associated either with concentration training or relaxation training depending on the therapeutic purpose of the game. In Figure 3, a change of the quantified level of the user concentration level is interpreted as a "faster/slower" movement of the "robot".

Figure 3: EEG-enable concentration "Dancing Robot" game.

The "Pipe" game is implemented more as a traditional neurofeedback game. In Figure 4, the "blue" bar located under the "green" bar on the screen shows the level of the user stress. In the "Pipe" game, water flows faster when the player's stress level increases, and hence it makes the game playing more difficult.

We also did preliminary study how to use the EEG-enable serious games for pain management and have got some promising results.

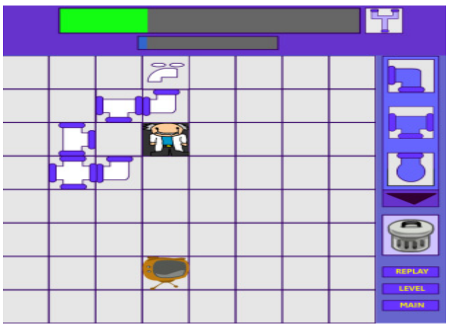
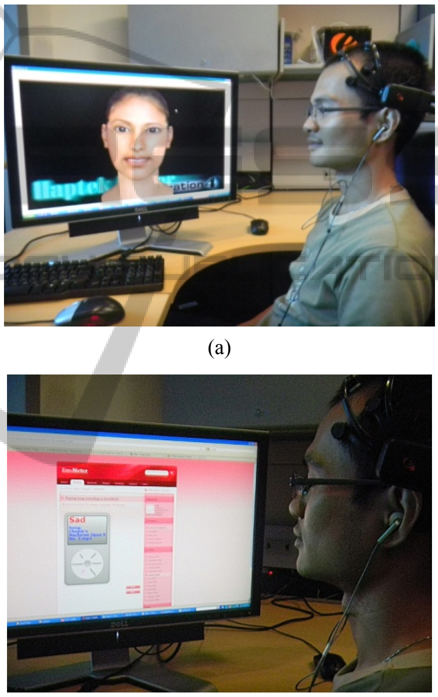


Figure 4: EEG-enable stress management "Pipe" game.

5.3 Emotion-based Digital Experience

We proposed and implemented a real-time fractal-based emotion recognition algorithm where the calculated fractal dimension values were mapped to 2D Valence-Arousal emotion model. It is possible to recognize in real time any discrete emotions that could be defined with the 2-dimensional emotion model. Satisfied, pleasant, happy, frustrated, sad, fear, and neutral emotions were recognized. In our algorithm, only 3 channels are used. We implemented two emotion-enable real-time applications. First, we implemented an application with the EEG-enable avatar (Liu et al., 2010). The music stimuli were used for emotion induction as it was proposed in (Sourina et al., 2008). We used an avatar available with free version of Haptek development package for our application (Haptek).



(a)

(b)

Figure 5: Emotion-enabled applications: a) "Pleasant" emotion is recognized and visualized on the user 3D avatar; b) "Sad" emotion is recognized and sent to the music therapy Web site.

Haptek Activex control provides functions and commands to change facial expressions of 3D avatars. 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. In the application, emotions of the user are recognized from EEG and visualized in real-time on the user's avatar with Haptek system. In Figure 5(a), the user was listening to music pieces for emotion induction, and the algorithm recognized "pleasant" emotion that was visualized on the user's avatar. The avatar emotions are changed according to emotions that the user is feeling during the music listening. Second, we implemented an EEG-enable music therapy website. The user/patient's emotion is recognized from EEG, and the corresponding music piece is downloaded according to the emotion recognized from the EEG of the user. In Figure 5(b), emotions are induced by music stimuli played through the earphone, and then the "inner" user's emotion is recognized from the EEG signal in real-time. Then, a pleasant song is played to the user upon recognizing the user is being sad to improve his/her mood or the corresponding music is played to calm down the user if he/she is too excited (happy or angry) or too nervous feeling "fear" emotion. A simple music therapy algorithm was proposed allowing automatically down load the corresponding music piece based on the recognized emotion to change the user mood. The choice of the appropriate music from the list could be given the user as well.

6 CONCLUSIONS

In this paper, we proposed and described a novel spatio-temporal fractal based approach to study different brain states such as concentration levels, human emotions, and in future other brain states such as "central pain" feeling, attention levels, etc. Using just one fractal dimension feature per channel and the simple machine learning algorithm allows us to implement real-time brain recognition applications with acceptable accuracy that could be improved by subject-based training. We expect further use of the proposed approach in different real-time applications. It could be also used in studies such as validation of the hypotheses: emotion induction could change pain level in the patients; the positive emotions could improve human performance, etc. We also work on the improvement on the real-time filtering of artefacts of different origin. The work described in the paper is a part of the project EmoDEx presented in (IDM-Project, 2008).

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