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ORIGINAL PAPER

Real-time EEG-based emotion recognition for music therapy

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Abstract Music could change our emotions, could have an influence on our mood, and finally could affect our health. Music therapy is one of the oldest methods used for treating some diseases. Since music therapy is proved to be the helpful approach, we proposed to combine music therapy process with the real-time EEG-based human emotion recognition algorithm. By this, we could identify the user's current emotional state, and based on such neurofeedback we could adjust the music therapy to the patient's needs. The proposed emotion recognition algorithm could recognize in real-time six emotions such as fear, frustrated, sad, happy, pleasant, and satisfied. As the algorithm is based on an Arousal-Valence emotion model, it has a potential to recognize all emotions that could be defined by the 2-dimensional model. The experiments on emotion induction with sound stimuli from International Affective Digitized Sounds (IADS) database and with music stimuli and implemented questionnaire were proposed and realized. In this paper, we proposed a general EEG-enabled music therapy algorithm. It allows us to adapt the therapy to the predefined time of the treatment and adjust the music therapy session to the current emotional state of the user in a way as an experienced music therapist works.

Keywords Real-time emotion recognition · EEG · Music therapy · Fractal dimension · HCI · BCI

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1 Introduction

Real-time EEG-based emotion-enabled interaction could add a new dimension in human computer interfaces opening endless possibilities of EEG-based application implementations for marketing, entertainment, and medical applications. In human-computer interfaces, an emotional state of the user could be recognized in many ways, for example, from face and/or gesture of the user, from the text, from the speech, or by biofeedback. The most valid and reliable emotion recognition algorithms could be EEG-based algorithms. The user's facial emotional expressions or his/her speech or the text typed by the user could be changed by the user intentionally. The EEG signals could reflect the "inner" true emotions of the user that could be very important, for example, in medical applications or product marketing applications. In work [9], we proposed and implemented a novel real-time emotion recognition algorithm. In this paper, we proposed a general EEG-based adaptive music therapy algorithm and based on it an EEG-enabled music therapy system was implemented. The following emotions such as fear, frustrated, sad, happy, pleasant, and satisfied could be recognized from the user's EEG in real time. As the emotion recognition algorithm is based on Arousal-Valence emotion model, it could be possible to recognize all emotions that are defined by the 2-dimensional model.

In this paper, in Sect. 2.1, we review on music therapy approaches. In Sect. 2.2, review on emotion classifications is given. In Sect. 2.3, emotion induction experiments with sound and music stimuli are introduced, and in Sect. 2.4, emotion recognition algorithms from EEG signals are reviewed. Fractal-based approach is described in Sect. 2.5. In Sect. 3, a fractal dimension based real-time emotion recognition algorithm, emotion induction experiments with sound and music stimuli, data analysis and results are given. A gen-

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eral EEG-based adaptive music therapy algorithm and music therapy website are proposed and described in Sect. 4. In Sect. 5, conclusion and future work are given.

2 Related works

2.1 Music therapy

The clinical use of music could be traced back in history. Music therapy was applied during wars to calm down the soldiers who were suffering from shell shock [28]. Generally, applications of music in the medical areas form four main directions [43]: (1) In functional occupational therapy, music is prescribed to help the patients exercise the joints and muscle. (2) In psychiatric treatment, music could help to relieve patients' tension and to distract their attention from the health problems. (3) In anesthesia, music listening could be used in the operating room during surgery to reduce amount of anesthetics needed during the operation or during baby delivery. (4) In hospital environment, music therapy could be used as psychological treatment to help the patients relax during any medical procedures [16] or when they are waiting for the medical procedure [15, 46].

Music therapy is a psychosocial intervention which gets more and more attention from the researchers in medical area. Nowadays, music therapy is defined by the American Music Therapy Association as "an established health service similar to occupational therapy and physical therapy" [3].

When a music therapy is administrated to the patients, therapists are always needed "to assess emotional well-being, physical health, social functioning, communication abilities, and cognitive skills through musical responses" [3]. Real-time emotion recognition from EEG could enhance music therapy process involving assessment of the emotional states of the patients and could reduce the need for the nurse staff participation.

2.2 Emotion models

Researchers classify emotions from different perspectives. For example, Plutchik [27] proposed the psycho evolutionary theory of emotion classification, in which eight primary emotions are defined as follows: anger, fear, sadness, disgust, surprise, anticipation, acceptance and joy. Then, the emotions such as love, awe, disappointment can be composed from the basic emotions.

Another emotion model is called the bipolar model of emotion, and it was proposed by Russell [29]. Here, two dimensions such as arousal and valence were used to describe emotions. The arousal dimension denotes the emotional property ranging from not aroused to excited, while the valence dimension denotes the emotional property ranging from not pleasant to pleasant. For example, sad is considered as a state with a relatively low arousal level and unpleasant valence level [30]. Despite the two dimensions in the bipolar model, there is the third emotional dimension called the dominance emotion dimension [24]. It ranges from the feeling of being in control during the emotional experience to the feeling of being controlled by the emotion [5]. When two emotional states are defined in the two dimensional model and have similar arousal and valence values, the third dimension could be added to differentiate the emotions. For example, fear and angry are both high aroused and negative emotions, however, fear is an emotion that cannot be controlled, and anger is more controlled emotion [9].

In general, the dimensional emotion classification is more widely used in the emotion recognition experiments since the emotion labels such as joy, surprise, etc. can be located in the dimensional space, and the dimensional view of emotion classification can enable the continuous emotion definition [9, 23].

2.3 Emotion induction experiments by audio stimuli

Emotions can be evoked by different external stimuli such as pictures, music, movies, etc. Here, we review the experiments with music and sound stimuli. For investigation of emotions, the International Affective Digitized Sound system (IADS) [8] is often used. The database provides standard audio stimuli in the form of sound clips. All sound stimuli from IADS are labeled with their arousal, valence and dominance level values. In work [6], the IADS database was used to elicit four emotions states which are positive/aroused, positive/calm, negative/calm and negative/aroused, and the corresponding EEG data labeled with the corresponding emotions were collected. The experiment protocol was designed as follows: five seconds exposure of the subject to the sound stimuli was followed by 10 seconds of silent/calm state of the subject.

Besides employing the IADS, there are works which were using the tagged music as audio stimuli to collect affective EEG signals. For example, work [19] induced four emotions such as joy, anger, sadness, and pleasure by using excerpts from Oscar films' soundtracks. The experiment procedure was designed as follows: 15 seconds of the subject exposure to the silent/calm state and then, the exposure to the 30 seconds of music. There are experiments that used combined visual and audio stimuli as well. For example, films were employed in the work [42] for affective EEG data collection.

Although when the stimuli are selected, there is a target emotion for each stimulus, the subjects feelings towards the same sound, music, or film could be subjective and may vary from the person to person. Thus, the self-assessment is needed for the subjects to be taken to describe their true feelings. Self-Assessment Manikin (SAM) technique [7] is a widely used one. It provides non-verbal pictorial assessment to evaluate emotions after the exposure of the subject to the stimuli. After carrying out the experiments to collect the raw EEG data and analyzing the self-assessment reports of the subjects, EEG data could be labeled with emotions.

2.4 Emotion recognition algorithms

Recently, new wireless and easy to install EEG devices appeared in the market. It made possible to work on real-time emotion recognition algorithms and EEG-enabled real-time games, medical applications, and even personalized digital arts installations. Although the real-time emotion recognition from EEG is a new area of research, there is established research on off-line EEG-based emotion recognition algorithms. In such algorithms, different approaches were investigated to extract the features from the raw EEG data and based on the features to classify EEG signals to the emotions classes. Emotion recognition algorithms could be classified by number of electrodes used, features calculated and types of classifiers applied. The electrode placement is done according to the American Electroencephalographic Society Standard [2], e.g. the locations of electrodes are named as AF3, F7, F3, etc. where the letters in the name represent notions for the different brain lobes, e.g. "F" stands for frontal lobe; the numbers in the name refer to the different locations in the particular lobe. In work [6], it was achieved the maximum accuracy rate of 97.4% for arousal levels recognition and the maximum accuracy rate of 94.9% for valence levels with Fpz and F3/F4 channels used. Work [33] obtained an accuracy of 62.07% to detect pleasant, neutral and unpleasant emotions with Short Time Fourier Transform approach for feature extraction and use of Support Vector Machine (SVM) as the classifier. Work [34] used peak alpha frequency, alpha power, and cross-correlation as the features and SVM as a classifier to recognize pleasant, neutral and unpleasant states, and the mean accuracy of 44.89% was obtained. Work [19] got the maximum averaged accuracy of 82.29% by employing the power division from 12 electrodes pair (e.g. power of Fp1 channel divided by power of Fp2 channel) as the features and the SVM as the classifier to recognize joy, anger, pleasure and sadness.

All the above mentioned works on EEG-based emotion recognition are subject-dependent ones. They emphasize that there are individual differences among different people. However, there are some works on subject-independent algorithms as well. Among those subject-independent works, [26] gives the best performance by using the Higher Order Crossings to extract the features and SVM as the classifier. In the work, an 83.33% maximum accuracy was achieved for differentiating the six emotions. Most of the proposed subject-dependent and subject-independent algorithms could be applied only for off-line processing due to the performance time. Real-time EEG-based emotion recognition algorithms with fewer electrodes, adequate accuracy and performance need to be developed.

2.5 Fractal dimension model

Fractal dimension (FD) values of EEG could reveal geometric complexity of the signals. It has been proved that FD could be applied in real-time EEG signal processing to identify different brain states [1, 20, 38]. Applications of fractal dimension in EEG analysis were given in [36, 37] where music was used to elicit emotions. In [39, 44] concentration levels of the subjects were recognized from EEG, and FD values were used as the classification features.

In our work, we proposed to use fractal dimension values as classification features in the proposed EEG-based emotion recognition algorithm. For calculation of fractal dimension value, we implemented and analyzed two well-known algorithms: box-counting [4] and Higuchi [17]. Both of them were evaluated using Brownian and Weierstrass functions where "true value" is known [22]. Higuchi algorithm was chosen to process the data since it gave a better accuracy as it was closer to the theoretical FD values [45] and it outperformed box-counting method in the processing of EEG data for emotion recognition [35].

Let us describe the Higuchi algorithm as we apply it for FD calculation in the fractal-based emotion recognition algorithm shown in Sect. 3.

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

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

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

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

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

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

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

Finally, the fractal dimension can be obtained by logarithmic plotting between different k and its associated $\langle L(k) \rangle$ [17].

3 Real-time emotion recognition from EEG

There is no easily available benchmark database of EEG data with the labeled emotions. In work [21], we designed and implemented two experiments to elicit emotions with audio stimuli. Five truncated songs which lasted for 1 minute each were used in the music Experiment 1. 10 participants, 2 female and 8 male students whose ages ranged from 23 to 35, participated in the experiment.

Sound clips selected from the International Affective Digitized Sounds (IADS) were used in Experiment 2. All the sounds in the IADS database were labeled with their arousal and valence values. As it was introduced in Sect. 2.3, IADS provides a set of standardized sound stimuli to evoke emotions that could be described by Arousal-Valence model. For example, positive valence and high arousal values define the happy emotion. 27 clips were chosen to induce five emotional states. 12 subjects, 3 female and 9 male students whose ages ranged from 22 to 35, participated in the sound experiment. None of the subjects participated in both experiments had history of mental illness. The procedures for both experiments are described as follows. After a participant was invited to the project room, he/she was briefly introduced to the experiment protocol and the usage of self-assessment questionnaire. Then, the participant was seated in front of the computer which played the audio stimuli. He/She was required to keep body still and eyes closed during the experiment sessions to avoid muscle movement and eye blinking artifacts.

Emotiv wireless headset [11] and PET 2 [25] were used to collect the EEG data. Finally, the Emotiv device was chosen for carrying out experiments as the Emotiv device is wireless and it is much easy to use. The proposed algorithm gave the similar results on the data collected with Emotiv device and with PET device. Emotiv device has 14 electrodes locating at AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 (CMS/DRL as references) following the American Electroencephalographic Society Standard [2]. The sampling rate of the Emotiv headset is 128 Hz. The bandwidth of the device is 0.2–45 Hz, and digital notch filters are at 50 Hz and 60 Hz. The A/D converter has 16 bits resolution. The data collected in two experiments using the Emotiv headset were analyzed to find spatio-temporal emotion patterns of high and low arousal level with positive and negative valence level and a fractal-based subject dependent algorithm was proposed and implemented in work [21]. A band-pass filter of 2 to 42 Hz 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 Sect. 2.5 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.

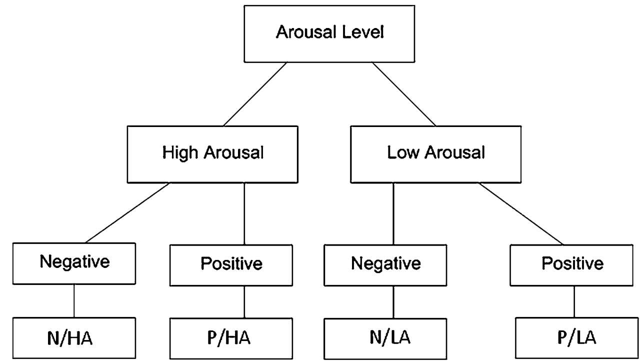

Fig. 1 The heriachical scheme of emotion recognition [21]

In our study, we analyzed the EEG data based on the feedback from the self-assessment questionnaire which gave us reflection of the subjects' feelings towards the audio stimuli. The FD values computed from the electrode FC6 was used to identify the arousal level ranging from low aroused to high aroused states. With the sliding window, we did offline processing to simulate the real-time emotion recognition. There were 46 comparisons of FD values between high and low arousal level from different subjects, and 84.9% of them show that larger FD values computed from FC6 are associated with higher arousal level [21]. The difference between FD values from the electrode pair AF3 (left hemisphere) and F4 (right hemisphere) was used to identify valence level and test the lateralization theory which suggests that right and left hemispheres are more active during negative and positive emotions respectively. 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. In Fig. 1, a hierarchical scheme we used to distinguish emotions is shown.

The results of the valence level recognition also revealed a partial support for the asymmetric frontal hypothesis. Although not all subjects' dominant hemisphere for positive or negative emotions was the same as expected in the asymmetric hypothesis [21], the pattern of lateralization for a particular subject was consistent among different experiments with similar arousal level. 10 subjects' data were available for comparison of positive and negative emotional states with similar arousal level. $9/10$ (90%) has shown the consistent pattern as follows. Five subjects had the larger difference of FD values between left hemisphere and right hemisphere (AF3-F4) during the experiencing of negative emotion, while 4 subjects had the larger difference of FD values when they experienced 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 [14] 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. As it was mentioned in Introduction, we follow two-dimensional Arousal-Valence model described in Sect. 2.2. This model allows the mapping of the discrete emotion labels in the Arousal-Valence coordinate system as shown in Fig. 2. 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 the 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.

The real-time EEG-based subject dependent emotion recognition algorithm is illustrated in Fig. 3. There are two part of this algorithm: the training session part and the emotion recognition part. Since there are individual differences of emotion patterns in the brain we need a short training session. In the training session, thresholds for each subject are calculated, and then they are used in the emotion recognition part. In Fig. 3, first, raw EEG signals are collected from AF3, F4 and FC6 channels and are filtered. After that, the FD values are calculated by Higuchi fractal dimension algorithm with a sliding window of 1024 samples size and 99% overlapping. For arousal level recognition, the FD values calculated from FC6 channel is used. In the training part, the EEG data are labeled with different emotional states, and the thresholds are calculated. In the recognition part, the newly computed FD value will be compared with the thresholds obtained from the training session. For the valence level recognition, the difference between two FD values computed from AF3 and F4 is calculated. In the training part, the lateralization pattern for each subject and the thresholds are defined. In the recognition part, the current arousal and valence levels are recognized in real time. Finally based on the arousal level and valence level, the emotions are mapped into 2D model.

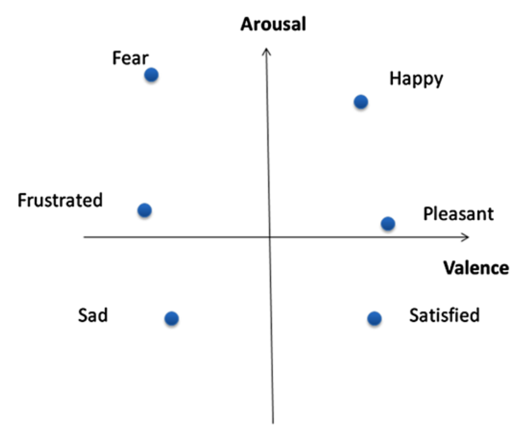

Fig. 2 Emotion labels in arousal-valence dimension (adapted from Russell's circumplex model [30])

4 Emotion-based music therapy

The real time EEG-based emotion recognition could be applied to many fields such as entertainment, education, medicine, etc. In our work, based on the proposed real-time emotion recognition algorithm we implemented a general EEG-based music therapy algorithm and then, an adaptive music therapy website.

4.1 Data acquisition

As it was described in Sect. 3, raw EEG data are acquired using Emotiv headset at 128 Hz frequency and Emotiv Software Development Kit. Three out of fourteen Emotiv's channels at the locations AF3, F4 and FC6 are fed into the emotion recognition algorithm in real-time. Generally, any EEG device with at least 3 electrodes located according to the proposed algorithm could be used.

Fig. 3 An emotion recognition scheme with training session [21]

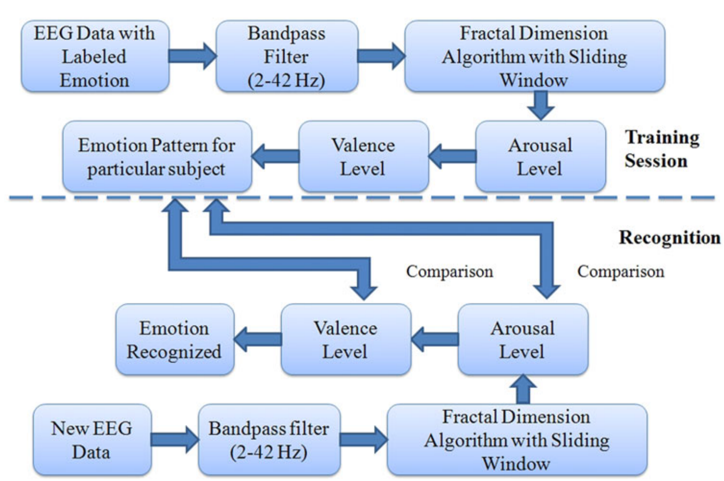

Table 1 Mapping of valence and arousal levels to the corresponding emotions

Label	(Valence, Arousal)	Emotion
1	(0, 0)	Sad
2	(0, 1)	Frustrated
3	(0, 2)	Fear
4	(1, 0)	Satisfied
5	(1, 1)	Pleasant
6	(1, 2)	Happy

4.2 Data processing

A data stream from the Emotiv device is copied to a buffer. As the fractal algorithm requires data to be fed in bunches of 1024 samples at the time point per one channel, we use a queue with size of 1024 to store the data from Emotiv's buffer to the algorithm. Every time a read command is triggered, the data in the buffer are taken out and put into the queue to replace the old data. Then a new FD value is computed by the refreshed data set in the queue. The number of data obtained to replace the old data in the queue at each time point depends on how many samples have been accumulated in the buffer.

To recognize emotion, FD values of arousal and valence levels are mapped into the discrete values using the emotions thresholds. After this step, the arousal level can only take one of the following values 0, 1 or 2 and the valence level takes 0 or 1 as shown in Table 1. Combination of the discrete values of arousal and valence levels gives us six types of emotions.

Music therapy is considered as an inexpensive and helpful approach in dealing with the patient's stress, anxiety and depression problems. By reviewing 29 peer works which focused on the investigation of the effectiveness of music therapy for hospital patients, [12] concluded that music therapy could effectively reduce the anxiety level, improve the mood of the patients and their tolerance to the pain. Other evidences of the effectiveness of the music therapy were given in work [41] where it was found that by playing music during the surgery, the anxiety level of the patients was reduced. In work [13], it was discovered that the anxiety level of Alzeheimer's disease patients could be reduced during the music therapy sessions. In [10], it was proved that pregnant women could also benefit from music therapy.

Usually the music therapy should have a therapist in attendance to adjust the therapy for each patient. Here, we combine the real-time EEG-based emotion recognition algorithm with the traditional concept of music therapy treatment and propose a novel general adaptive algorithm of music therapy treatment. Thus, the patients' current emotion is recognized from his/her EEG in real time, and the music therapy is adjusted automatically based on the feedback. We developed a general adaptive algorithm for music therapy which allows evoking and maintaining the targeted emotions in one therapy session according to the predefined time for each emotion. For example, during one treatment, pleasant emotion is kept for 10 minutes, followed by happy emotion for 15 minutes, and pleasant emotion is kept for 10 minutes at the end. The whole therapy could be seen as a composition of small sessions with different targeted emotions and the predefined time duration of each targeted emotion. The developed algorithm could be described as follows.

First, the type of music therapy is selected from the set: $type = \{anxiety, depression, pain, \ldots\}$. Then, based on the type of the music therapy, the following information is obtained:

(1) The sequence of the targeted emotions in the therapy.
(2) The corresponding time for each targeted emotion in the sequence.

After obtaining the above information, the algorithm within each small session aims to evoke the emotion during the predefined time and could be described as follows.

(1) Music from the music database corresponding to the targeted emotion is selected automatically.
(2) A timer is initialized to count the time of the targeted emotion state: $t = 0$.
(3) The current emotion of the patient is assessed from his/her EEG in real time. If the target emotion is successfully elicited, this music is kept playing during the predefined time. If the targeted emotion is not induced it is changed to another piece of music from the music database. When one piece of music is over, another piece of music is played to evoke the targeted emotion during the predefined time.
(4) When the targeted time is over, the session ends.

For the next targeted emotion in the list, another session starts and follows the steps 1 to 4. The pseudo code of the proposed adaptive EEG-based music therapy algorithm is given as an Algorithms 1 and 2. The Algorithm 1 is an information acquisition algorithm. The type of music therapy is chosen by the patient and the output of the algorithm is a $n * 2$ matrix defining sequence of the targeted emotions in the chosen therapy and the time duration associated with the corresponding emotion in the sequence. The Algorithm 2 follows the steps 1–4 described above to evoke the targeted emotion during the predefined time.

We designed and implemented the EEG-enabled music therapy website as shown in Fig. 4. In Fig. 4, the user with the Emotiv headset is shown. The user's "inner" emotion is recognized from EEG in real time and entered into the music therapy algorithm. The real-time EEG-based emotion recognition algorithm is packaged as an ActiveX Component by Visual C++. Currently, we have 3 types of music therapy.

Algorithm 1 Information acquisition algorithm

Input: *Type* {The type of therapy selected}
Output: *infoMatrix* {2D matrix contain the sequence of emotions and their corresponding length of duration for the selected therapy}
$n \leftarrow$ getEmoNum(*Type*) {Get the total number of emotion types in the current therapy}
for all i such that $1 \le i \le n$ **do**
  {Get the emotion labels and their corresponding duration in order}
  $infoMatrix_{i1} \leftarrow$ getEmoLabel(*Type*)
  $infoMatrix_{i2} \leftarrow$ getTimeLength(*Type*)
end for
return *infoMatrix*

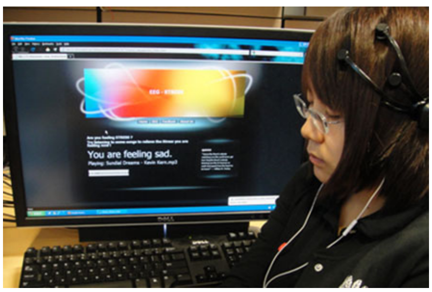

Fig. 4 The user with EEG-enabled music therapy website

The first one deals with pain problems as follows: the music pieces targeting a happy emotion are played to the patient to destruct his/her attention from the pain. This strategy is in accordance to work [40]. The second type of therapy deals with depression. Here, the songs targeting the sequence of sad, pleasant, and satisfied emotions are played to the user. The third type of therapy is to reduce an anxiety level of the patient. The music pieces targeting the sequence of satisfied, pleasant, satisfied, and pleasant emotions are played to the patient/user. The music pieces are adjusted according to the real-time EEG-based emotion recognition.

Algorithm 2 Music therapy algorithm

{Get the column number of the information matrix}
$n \leftarrow$ size(*infoMatrix*,1)
for all i such that $1 \le i \le n$ **do**
  {Get the target emotion label in series}
  $targetEmo \leftarrow infoMatrix_{i1}$
  {Get the time duration of the targeted emotion}
  $t1 \leftarrow infoMatrix_{i2}$
  {Select the music corresponding to the targeted emotion}
  MusicID $\leftarrow$ getMusic(*targetEmo*)
  {Get the size of the music database of the targeted emotion}
  size $\leftarrow$ getSize(*targetEmo*)
  {Initiate the timer counting the time duration of the therapy to 0}
  $t \leftarrow 0$
  while $t \le t1$ **do**
    play(*MusicID*) {Play the chosen music}
    {Check the patient's current emotion by the real-time EEG-based emotion recognition algorithm}
    EmoCheck $\leftarrow$ emotionRecog(*EEG*)
    if *EmoCheck* is not equal to *targetEmo* **or** reach the end of one piece of music **then**
      if $musicID < size$ **then**
        {Change to another music}
        $musicID \leftarrow musicID + 1$
      else
        {Initialize the music database}
        $musicID \leftarrow 1$
      end if
      play(*musicID*)
    end if
    {count the efficient time slice of each music played}
    $te_i \leftarrow$ length(play(*musicID*))
    {cumulate the timer}
    $t \leftarrow t + te_i$
  end while
end for

5 Conclusion and future work

Real-time EEG-enabled human computer interaction could add a new dimension to human computer interfaces. In this paper, we proposed a novel general EEG-enabled music therapy algorithm and implemented an adaptive music therapy system that could be used by the patient/user without any help from a music therapist. Compared with the traditional music therapy, our proposed EEG-based music therapy does not need a therapist to be in attendance, and the therapy is an adaptive one—it is personalized to each individual patient. The algorithm is based on the real-time subject-dependent fractal-based emotion recognition algorithm. Six emotions such as fear, frustrated, sad, happy, pleasant, and satisfied could be recognized in real time and could be used in the music therapy system. There is a choice of different therapies targeting stress management, pain management, depression, stroke rehabilitation, etc. The therapy is defined by sequence of the targeted emotions and duration of each emotion that should be advised by the therapist. Thus, any therapy could be introduced and added to the system.

At the current stage, the proposed EEG-based music therapy has not been tested on patients, however, in future, we are planning to do experiments on assessment of the proposed music therapy.

Short videos about the applications based on the real-time emotion recognition algorithm including the Music Therapy website, and more information about the project EmoDEx are presented in [18].

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