Music Mood Detection Using EEG

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Abstract*-Human emotions classification based on electroencephalogram (EEG) is discussed in this paper. An EEG is a test used to evaluate the electrical activity in the brain. Brain cells communicate with each other through electrical impulses. An EEG tracks and records brain wave patterns. Small flat metal discs called Electrodes are attached to the scalp with wires. 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(tone), facial expressions or gestures. This paper is concentrated on recognition of "inner" emotions from electroencephalogram (EEG) signals. Analysis of human mood can be done using real-time fractal dimension based algorithm of quantification of basic emotions using Arousal-Valence emotion model, whereas, using algorithm which analyzes the audio properties, features can be extracted for generating automatic playlists representing different moods.*

Keywords-EEG, Electrodes, Emotion Recognition, Fractal Dimension algorithm, Arousal-Valence model, Audio Properties

I. INTRODUCTION

Nowadays, new forms of human-centric and human-driven interaction with digital media have the potential of revolutionizing entertainment, learning, and many other areas of life. The need and importance of automatic emotion recognition has grown with an increasing role of human-computer interface applications as emotions play an important role in day-to-day life. Emotion recognition could be done in many ways such as by using text, tone, facial expressions or gestures, but, recently more researches were done on emotion recognition using EEG. 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 the areas such as entertainment, E-learning, virtual worlds, cyber worlds, etc. Automatic emotion recognition from EEG signals is receiving more attention with the development of new forms of human-centric and human-driven interaction with digital media.

Overall hypothesis is that the feeling of changes can be noticed from EEG as fractal dimension changes. Study is focused on fractal dimension model and algorithms for emotion recognition. There are 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 the 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 offline data processing. Also an EEG-based music therapy and a music player are implemented with real-time emotion recognition algorithms. Although in this paper, standalone implementations of emotion recognition and its applications are described, it could be easily extended for further use in collaborative environments or cyber worlds.

II. LITERATURE SURVEY

EEG WAVES

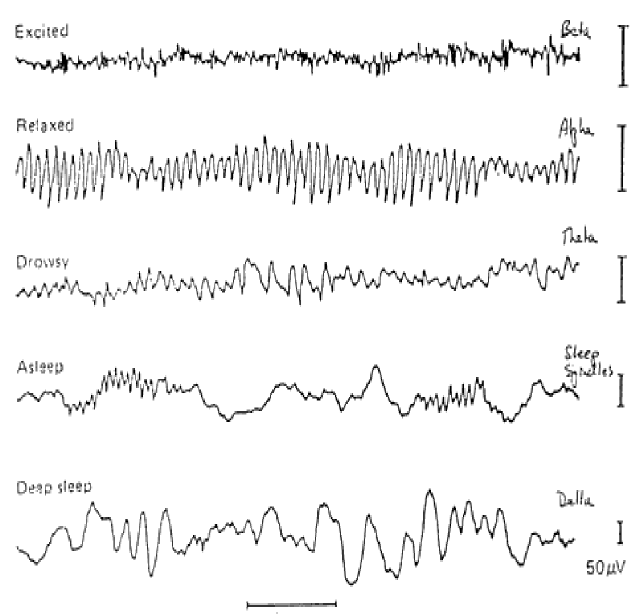

Fig. 1 EEG Waves

EEG waveforms as shown in fig. 1 are generally classified according to their frequency, amplitude, and shape, as well as the sites on the scalp at which they are recorded. The most familiar classification uses EEG waveform frequency (e.g. alpha, beta, theta and delta).

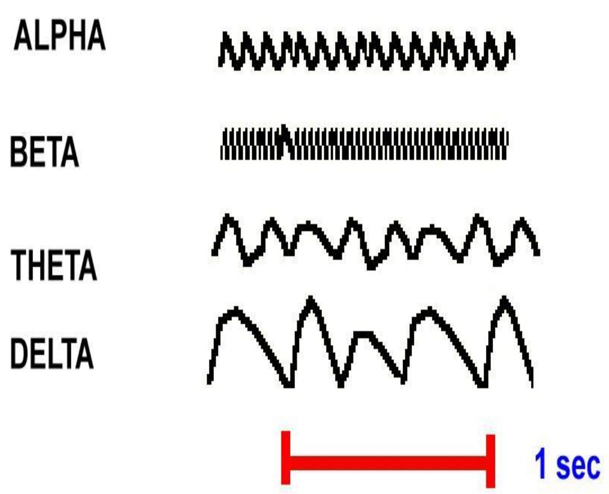

Fig. 2 Classification of EEG Waves

Information about waveform frequency and shape is combined with the age of the patient, state of alertness or sleep, and location on the scalp to determine significance. Normal EEG waveforms, like many kinds of waveforms are defined and described by their frequency, amplitude and location. Frequency (Hertz, Hz) is a key characteristic used to define normal or abnormal EEG rhythms. Most waves of 8 Hz and higher frequencies are normal findings in the EEG of an awake adult. Waves with a frequency of 7 Hz or less often are classified as abnormal in awake adults, although they normally can be seen in children or in adults who are asleep. In certain situations, EEG waveforms of an appropriate frequency for age and state of alertness are considered abnormal because they occur at an inappropriate scalp location or demonstrate irregularities in rhythmicity or amplitude. Some waves are recognized by their shapes, scalp location or distribution, and symmetry. Certain patterns are normal at specific ages or resemble specific shapes, such as vertex (V) waves seen over the vertex of the scalp in stage 2 sleep or triphasic waves that occur in the setting of various encephalopathies.

Frequency

The frequency of brain waves ranges from .05-500 Hz. However, the following categories of frequencies, shown in fig. 2, are the most clinically relevant:

Alpha waves – 8-13 Hz
Beta waves – Greater than 13 Hz
Theta waves – 3.5-7.5 Hz
Delta waves – 3 Hz or less

Alpha waves

- Alpha waves generally are seen in all age groups but are most common in adults. They occur rhythmically on both sides of the head but are often slightly higher in amplitude on the non-dominant side, especially in right-handed individuals. A normal alpha variant is noted when a harmonic of alpha frequency occurs in the posterior head regions. They tend to be present posteriorly more than anteriorly and are especially prominent with closed eyes and with relaxation.
- Alpha activity disappears normally with attention (e.g., mental arithmetic, stress, opening eyes). In most instances, it is regarded as a normal waveform.
- An abnormal exception is alpha coma, most often caused by hypoxic-ischemic encephalogram of destructive processes in the Pons (e.g., intracelebral hemorrhage). In alpha coma, alpha waves are distributed uniformly both anteriorly and posteriorly in patients who are unresponsive to stimuli.

Beta waves

- Beta waves are observed in all age groups.
- They tend to be small in amplitude and usually are symmetric and more evident anteriorly.
- Drugs, such as barbiturates and benzodiazepines, augment beta waves.

Theta waves

- Theta waves normally are seen in sleep at any age. In awake adults, these waves are abnormal if they occur in excess.
- Theta and delta waves are known collectively as slow waves.

Delta waves

- These slow waves have a frequency of 3 Hz or less.
- They normally are seen in deep sleep in adults as well as in infants and children.
- Delta waves are abnormal in the awake adult.
- Often, they have the largest amplitude of all waves.
- Delta waves can be focal (local pathology) or diffuse (generalized dysfunction).

Generalized Block Diagram

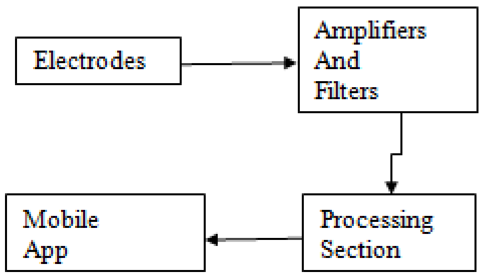

Fig. 3 Generalized Block Diagram

By referring [10], [11], and [13], one can get basic idea of overall system i.e. “Music Mood Detection Using EEG”. The typical block diagram related to this system, as shown in fig. 3, includes following sections:

Dry electrodes

Fig. 4 Dry electrodes

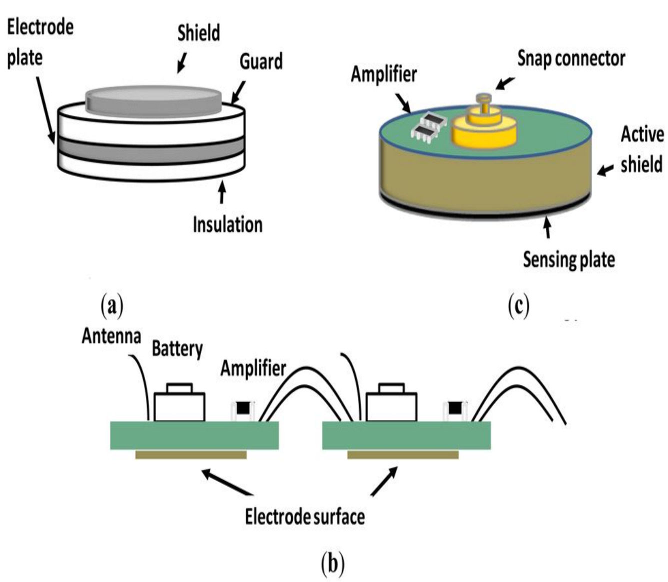

Fig. 5 Structure of Dry Electrodes

Typical EEG electrodes have two major mechanical and electrical restrictions, namely the size and impedance. The electric dipole caused by just one pyramidal cell cannot be measured with electrodes attached to the scalp. However, when a large number of dipole units, approximately 60 million synchronously discharges their action potentials, it gives rise to potentials in the scale of micro-volts, large enough to be measured with non-invasive methods. In summary, the EEG is the macroscopic measure of the synchronous activity of a large population of neurons. A theoretical estimate of the area required to cover this population is approximately 6 cm2. Current implementations are not far from this estimate. A typical diameter of an EEG electrode is 10 mm (1.6 cm2) and commercial products such as Quick-Cap use an effective size of 7 mm. In summary, innovative-dry approaches suffer from a severe restriction for miniaturization. The Dry EEG electrodes and general structure of EEG electrodes is as shown in fig. 4 and fig. 5 respectively.

Amplifiers and Filters

Generally, these EEG waves are in micro-volts range and so they can’t be studied as it is. As these waves have very less amplitude, they can get affected by noise. So, different stages of amplifiers are used which will amplify waves’ amplitude to a comparable range and will also provide high CMRR. The waves are in the range 1-30 Hz which is very less frequency range. So to prevent them from noise and to prevent output from unwanted signals different stages of filters are used.

Emotion Recognition Algorithms

There are an increasing number of researches done on EEG-based emotion recognition algorithms. Referring [3] and [6], Short-time Fourier Transform was used to calculate the power difference between 12 symmetric electrodes pairs with 6 different EEG waves for feature extraction and Support Vector Machine (SVM) approach was employed to classify the data into different emotion modes. The result was 90.72% accuracy to distinguish the feelings of joy, sadness, anger and pleasure. A performance rate of 92.3% was obtained in using Binary Linear Fisher’s Discriminant Analysis and emotion states among positive/arousal, positive/calm, negative/calm and negative/arousal were differentiated. SVM was applied for emotion classification with the accuracy for valence and arousal identification as 32% and 37% respectively. By applying lifting based wavelet transform to extract features and Fuzzy C-means clustering to do classification, sadness, happiness, disgust, and fear were recognized. 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 real-time EEG based emotion recognition and its applications. Using Relevant Vector Machine, differentiation between happy and relaxed, relaxed and sad, happy and sad with a performance rate around 90% was obtained.

A fractal dimension analysis is suitable for analyzing nonlinear systems and could be used in real-time EEG signal processing as mentioned in [2]. Early work showed that fractal dimension could reflect the change of EEG signal showed that fractal dimension varied for different mental tasks; a more recent work revealed that when brain processed tasks which were of emotional difference only, fractal dimension can be used to differentiate these tasks. By referring [7] and [9], one can conclude that, music is used as stimuli to elicit emotions, and applied fractal dimension for the analysis of the EEG signal and to detect the concentration level of the subjects. All these works show that fractal dimension is a potentially promising approach to investigate EEG-based emotion recognition. As per research, fractal dimension model is explored to provide better accuracy and performance in EEG-based emotion recognition. For calculation of fractal dimension value, implementation and analyzation of two well-known algorithms: box-counting and Higuchi is necessary. Both of them were evaluated using Brownian and Weierstrass functions where "true value" is known. Higuchi algorithm was chosen to process the data since it gave a better accuracy as it was closer to the theoretical FD values and it outperformed in the processing of EEG data.

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

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

Where m= 1, 2,…, k, m is the initial time and k is the interval time. Then, k sets of Lm(k) are calculated as follows:

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

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

$\langle L(k)\rangle \propto$ k-D .

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

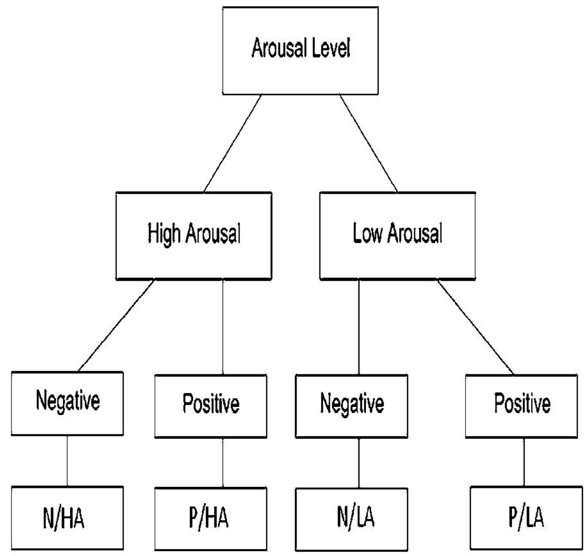

Fig. 5 Levels of Arousal

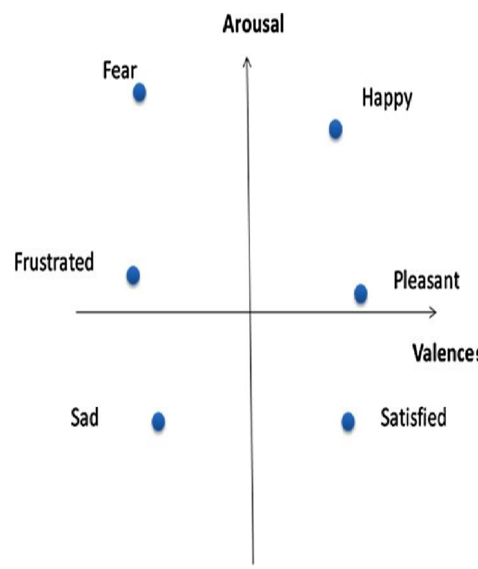

Fig. 6 Plot of Arousal Vs Valence

TABLE I
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

Automatic Playlist Generating Algorithm

This algorithm includes statistical features to classify music(standard deviations, etc) as follows:

- Tempo
- Sterio Panning Spectrum Features
- Mel Frequency Cepstral Coefficients
- Chroma
- Spectral Flatness Measure
- Spectral Crest Factor
- Spectral Centroid
- Spectral Rolloff
- Spectral Flux
- Line Spectral Pair
- Linear Prediction Cepstral Coefficients
- Zero Crossings

III. CONCLUSION

Electroencephalography belongs to electro-biological imaging tools widely used in medical and research areas. EEG measures changes in electric potentials caused by a large number of electric dipoles formed during neural excitations. EEG signal consists of different brain waves reflecting brain electrical activity according to electrode placements and functioning in the adjacent brain regions. In this paper, emotion classifications, emotion evoking experiments and emotion recognition algorithms were reviewed. Fractal dimension based algorithm for recognition of emotions from EEG in real time is described. Approach is based on FD calculation allows recognize even more emotions that can be defined in 2-dimensional Arousal-Valence model. This system will provide better enjoyment to the music listeners by providing the most suitable or appropriate song to the user according to his current mood. Paper presents a proposed system and an approach for the automatic creation of mood based playlist. The proposed system will reduce the efforts of user in creating and managing playlist it will not only help user but also the songs are systematically sorted.

ACKNOWLEDGEMENT

It gives me an immense pleasure to present the report of our project here. It has been quit experience, facing a number of problems at stages and coming up with appropriate solutions, at time the discussion amongst us or suggestions from our friends and teachers.

We thank Prof. G. S. Kulkarni (H.O.D. Electronics and telecommunication Dept.) for giving us this opportunity to develop and enhance our practical skills and knowledge.

We thank our guide Prof. S. V. Chougule for helping us in the best possible way to reach this stage.

Lastly, we would like to put our thanks on record to the teaching and non-teaching staff of all faculty members for rendering their support directly or indirectly.

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