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Music Therapy by Analyzing EEG Signals

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Abstract: The role emotions play in our life is inevitable right from the way we interact with other humans, in our decision-making process and even in the way we see the people around us. In this technological world, human computer interaction is almost everywhere. Right from fingerprint access in our mobile phones to face recognition- based attendance patterns at work places, human computer interaction has formed a strong base in day-today activities of human life. In such human computer interaction, EEG has gathered attention since it can provide simple, cheap, precise methods of emotion recognition. In this proposed work, a Music app is created which plays songs based on the emotion recognized from the given EEG signal. In MATLAB, the trained EEG signals are given and it is further processed to extract the features. The extracted features are classified to find the emotion and the result is sent to the music app. The music app which contains the playlist plays accordingly.

Keywords: EEG, MATLAB, Emotion recognition, Feature extraction.

1. Introduction

Our Emotion plays an integral part of our life. Real time estimation and adjustments will boost people's life and will make their life better. For instance, emotions will play a better role of communicator in the field of Human Computer Interaction. In Medical field, for the treatment of patients whose issues are regarding expressions, Emotions will find a remarkable way to help the diagnosis of the patients. Without processing emotions computers cannot communicate with humans effectively. Emotions are the basic tool of Emotional Intelligence. In recent times efforts are being made to enhance the communication between computers and human through Human Computer Interface. Affective Computing has grown in order to build a model to determine the state of a person, which will be acting as a major contributor in Human Computer Interface [1].

The emotional condition of a person is usually influenced by the subjective experiences, internal feelings (physiological signals) and also by the surroundings (external factors). Self-reports can inform beneficial information because one may not respond how they are feeling exactly, rather they would respond in a way other would like them to. Hence physiological signals contribute here for an improved understanding of the emotions. Physiological signals are the multi channel recordings from the central nervous system and autonomic nervous systems. Brain and Spinal cord form the central nervous system whereas the autonomous nervous system includes the system which acts unconsciously such as pupillary response, heart rate etc.

The readings measured from the brain also are helpful in studying emotions. The available neuron imaging techniques are EEG, MRI and PET.

EEG is primarily detection of activity of the place at which the electrodes are kept. The characteristics of the signal differ based on the place where the electrode is kept.

Based on the frequency ranges, the EEG can be classified into 5 types which is shown in figure 1.

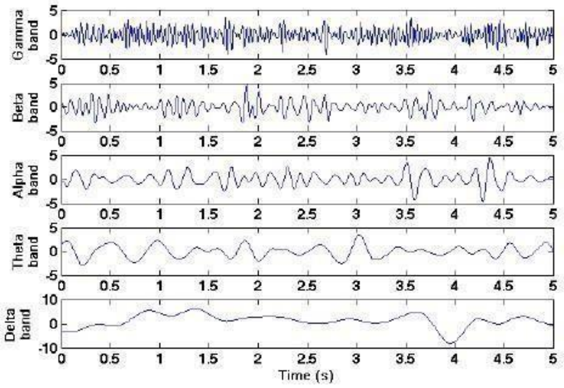

Figure 1. EEG Signals

Based on the frequency ranges, the EEG can be classified into 5 types.

1. Delta waves of the range 0.5 - 0.4 Hz
2. Theta waves of the range 4 - 8 Hz
3. Alpha waves of the range 8 – 13 Hz
4. Beta waves of the range 13 – 30 Hz
5. Gamma waves of the range 30 – 128 Hz

In recent times emotion recognition [2] using EEG has drawn the notice of many eminent scholars right from psychology to engineering fields. Using EEG based emotion recognition [3] computers can look into the human brain and it can determine the user's state. Hence to moves towards a convincing Human Computer Interface we need to build a reliable emotion recognition system.

The emotion has to be categorized from the features of the EEG signals. In this proposed model, to construct a reliable emotion recognition model the collected EEG signals were analysed and neural networks were used to classify the emotions. In this proposed method, emotion recognition is done using MATLAB software. The recognized emotion is sent to Bluetooth via Raspberry Pi 3. Through the Bluetooth, the music app acquires the state and plays the stored songs as a therapy to the user.

2. Existing System

Music makes our life lovely and the mental state of people is impacted in a different way for everyone. Most of the related works use voice recognition or speech analysis. In these models, the emotions of the subjects can be undisclosed either intentionally or unintentionally. Music has the capability to act as therapy when properly matched with the state of the subject [4]. In the present-day music systems, songs are played manually without proper inter relation with the emotional state of the user. Hence there is a need for emotion classification. The acuteness between emotions is difficult to arrive at because everybody has their own way of expressing their emotions. [5] To model the emotions few researches have proposed models which apply the two-dimensional modeling because of its simplicity and signal processing techniques.

3. Proposed System

In this proposed model we used trained EEG signals from which noise were removed using Image Processing Techniques and segmentation was done. The statistical features were extracted by performing statistical analysis [6] with the help of Discrete Wavelet Transform and Principal Component Analysis [7, 8] in MATLAB. These extracted features were used to classify [9] the emotion. Overview is presented in the block diagram in fig. 2.

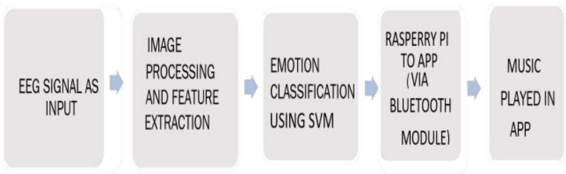

Figure 2. Block diagram of Proposed Model

4. EEG Signal Analysis

Data Acquisition:

The EEG signal is acquired primarily through EEG electrodes and EEG headsets [10]. Since this experiment focuses on Image processing and App development, a dataset which was obtained through clinical sources was used and the dataset was further trained to reduce the artifacts. Thus, a trained dataset was ready for the experimental purpose.

The fig.3 shows the sample trained EEG signal which was further used for processing

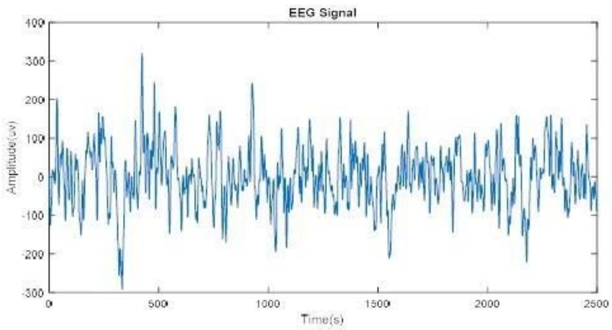

Figure 3. Trained EEG Input

Image Processing and Feature Extraction:

Once the trained dataset was obtained, they were loaded into MATLAB software for further processes. Median filter function from MATLAB was used to remove the noises present in the edges and it was the basic step for pre-processing of EEG signals.

CNN Convolution was done to recognize pattern of the signals and they provided good pattern recognition results as this CNN directly learns from the images. K means clustering was used in this process to group the data into similar and dissimilar patterns. The results were stored. The processed signals were further used for feature extraction using DWT and statistical analysis.

Discrete Wavelet Transform:

Images are made up of pixels which contain the digital information about the intensity of the corresponding images. This information about pixels are stored in matrices in the spatial domain and are very much repetitive. Hence there is a need to remove this repetitive information through image compression techniques for better storage and computations. Discrete Wavelet Transform (DWT) [11] has become the most used Image compression technique because of its Multi resolution analysis and its ability to decompose signals into sub-bands. In this work, Discrete Wavelet Transform [12] is implemented for image compression as this method provides clear information about the sudden occurring transient changes in EEG. Other important feature of DWT is that, it provides precise details in both time and frequency scale, so that no information is lost. By using this wavelet transform technique, the pixels that are stored in spatial domain are converted to frequency domain information, which are shown as sub-bands and also are represented in frequency and time scales.

Wavelet transforms are very often used to represent the non-stationary signals in real time with much improved efficiency. Wavelet transform decomposes the images into many sets of functions, called as wavelets. These wavelets store information about the images more precisely than the pixel blocks. Also, these wavelets show the clear changes in tones, colors of the images and also, they provide results in very small JPEG files with better efficiencies. In DWT, the input signal is usually convolved in the cutting window known as Mother Wavelet. The convolution between the input signal and the specified filter co-efficient provides us with the necessary frequency information.

In this work, 2D-DWT [8] was performed which decomposes the signals into coefficient of the wavelets and scaling functions. 2D- DWT is performing 1D-DWT along the rows in the first step and then performing 1D-DWT along the columns as the second step. An array transposition is added between both the 1D-DWT. Initially, 1D-DWT is done for rows of the array, as a result, the array gets split into two vertical halves. The first half of the array contains the absolute co-efficient, while the second half contains the detailed co-efficient. Then the same process is extended to the columns. In this work, three level decomposition is done and the detailed coefficients obtained are D1-D3 and A3 is the obtained absolute coefficient.

The function used in MATLAB to perform 2D- DWT is

[cA,cH,cV,cD] = dwt2(X, wname) …… (1)

The wavelet used was Daubechies wavelet db4. By this way, we get a set of Detailed coefficients, Absolute coefficients, Horizontal and vertical coefficients. These values are closely correlated and mostly repetitive. Hence these values are sent for an analysis method called as Principal Component Analysis (PCA).

G= pca(DWT_feat) ……(2)

The above formula was used in MATLAB to implement Principal Component Analysis.

By using PCA [7], the variables can be reduced into few Principal Components based on the weightage of the variables. Now these variables are sent for feature extraction using statistical analysis [6].

Feature Extraction:

Using Mathematical Computations, the EEG image was used to extract the following statistical features.

1) Skewness:

Skewness is a measure of symmetry of a probability distribution. Mean and variance has to be found before finding skewness.

$$g = \sqrt{\frac{\sum_{i-1}^{n}(x - x_i)^3}{(n-1)\,s^3}}$$ ……… (3)

2) Kurtosis:

Kurtosis is a measure of whether the data are heavy-tailed or light-tailed. Data sets with low kurtosis tend to have light tails, or lack of outliers and vice versa.

Kurtosis is represented by the formula,

$$g_2 = \frac{1}{n}\sum_{i=1}^{n} z_i^4 - 3$$ ……… (4)

3) Correlation:

Correlation is the process of moving a filter mask over the image and computing the sum of products at each location.

$$\sum_{i,j}\frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i\sigma_j}$$ …….. (5)

4) Energy:

Energy a function that would capture the solution we desire and perform gradient descent to compute its lowest value, resulting in a solution for the image segmentation.

$$\sum_{i,j} p(i,j)^2$$ ……… (6)

5) Homogeneity:

Returns a value that measures the closeness of the distribution of elements in the GLCM to the GLCM diagonal.

$$\sum_{i,j}\frac{p(i,j)}{1+|i-j|}$$ ……… (7)

6) Contrast:

Returns a measure of the intensity contrast between a pixel and its neighbor over the whole image. The property Contrast is also known as variance and inertia.

$$\sum_{i,j} |i-j|^2 p(i,j) \quad \text{......... (8)}$$

7) Entropy:

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image.

-sum (p.*log2 (p)) …… (9)

8) Mean and Variance

Mean value gives the contribution of individual pixel intensity for the entire image & variance is normally used to find how each pixel varies from the neigh boring pixel (or centre pixel) and is used in classify into different regions

$$\text{variance } \sigma^2 = \frac{\sum_{i=1}^{n} (x_i - \bar{x})^2}{n} \quad \text{..... (10)}$$

9) Smoothness:

Smoothing is often used to reduce noise within an image or to produce a less pixilated image**.**

All these above features were implemented in MATLAB using the inbuilt functions available.

Feature Classification:

In this method SVM was used as a classifier [9]. It is a machine learning algorithm used to solve problems of classification. In this classifier, the extracted features are taken as input and are projected on a higher dimension plane through RBF kernel functions. The input data was iterated many times till they got separated distinctly by the hyper planes.

In this work, a 10-fold cross validation was implemented to divide the data set into few subsets. Once they were separated, the hyper planes acted as the boundaries to make decisions and with the help of SVM, the trained data were classified into happy, anger and sad. Further the result was displayed in MATLAB and the result was transmitted through Bluetooth to the MUSIC APP.

5. Result & Discussion

The result of Angry State is shown in the figure 4. It includes the image of the original EEG input signal and the plot of addition of salt and pepper noise. The removal of the added noise through median filter is shown in the next plot and the output of Segmentation is also displayed. Then, through feature extraction [13, 14, 15] and SVM classification the output state is determined as Angry in MATLAB.

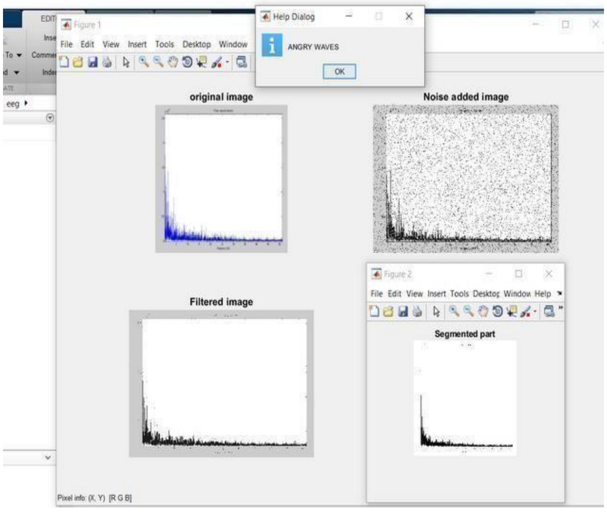

Figure 4. MATLAB Output

The output is then sent to the raspberry pi for further processes which is shown in figure5.

The transmitter of the USB TTL of system is connected to the board. The output is connected to the transmitter of Bluetooth module through another USB TTL. The receiving and transmitting program of Emotional state is written in Python language. In IF CASE, it is coded that if the Raspberry Pi receives A through its serial port, it must transmit the state 'Happy'. Similarly, the IF CASE is extended for Sad and Angry states.

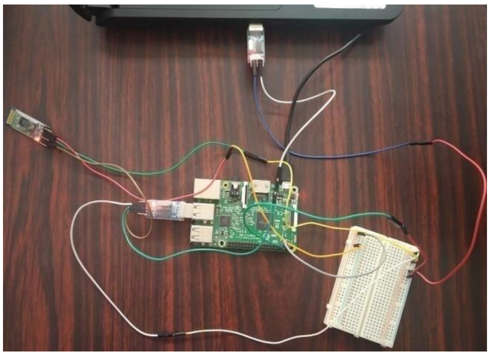

Figure 5. Experimental Setup

The music app is developed using the Android studio app. The tune is available for three types of mood is classified in our music app. The process of customization of APP is shown in the figure6.

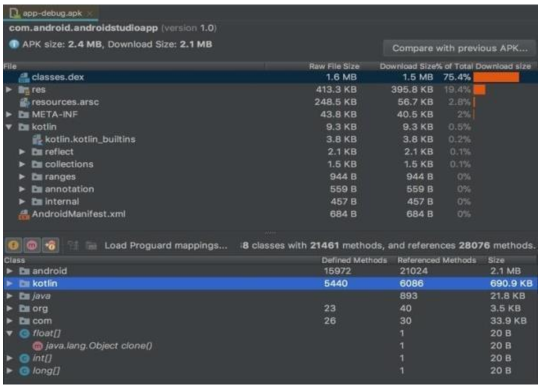

Figure 6. Customization of APP

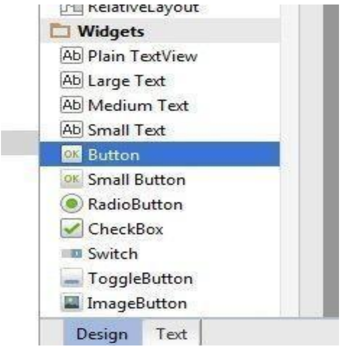

Figure 7. Creation of buttons in Android Studio

The process of creating buttons in Android Studio for our app is shown in the figure7.

The development of Music app in Android Studio is shown in figure 8.

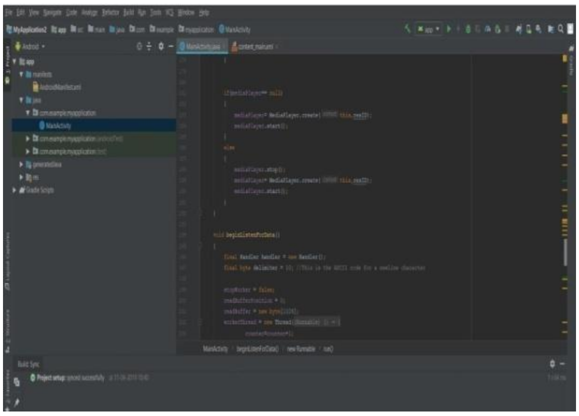

Figure 8. Development of Music App

Figure 9 shows the final app created using the Android studio to provide music therapy.

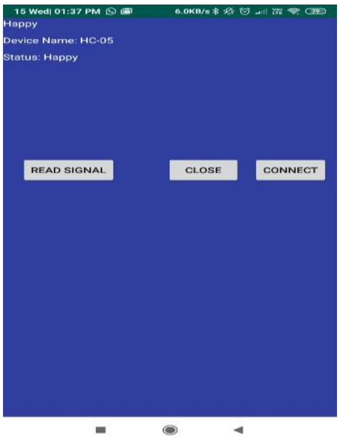

Figure 9. Music app

6. Conclusion

In this proposed work, we processed the EEG signals and the noise in the signal was removed. The processed EEG signal provided necessary features to determine the emotion from EEG. The determined emotion was sent to our Music Therapy App through Bluetooth and the stored songs were played accordingly to each emotion.

7. Future Scope

The enhancement of the current system can be done by acquiring the EEG signals in real time. The app can be made more user interfaceable. History of emotions can be made available by making use of cloud application.

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