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Music induced emotion using wavelet packet decomposition—An EEG study

Geethanjali Balasubramanian[a], Adalarasu Kanagasabai[b,*], Jagannath Mohan[c], N.P. Guhan Seshadri[a]

[a] Department of Biomedical Engineering, SSN College of Engineering, Chennai, Tamilnadu, India
[b] School of Electrical and Electronics Engineering, SASTRA Deemed University, Thanjavur, Tamilnadu, India
[c] School of Electronics Engineering, Vellore Institute of Technology (VIT) Chennai, Tamilnadu, India

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ABSTRACT

Music has the potential to invoke strong emotions, both positive and negative, wherein positive emotions can augment well-being. The objective of this study was to analyze the dynamic emotional responses of the participants to self-selected music using Electroencephalography (EEG). The frequency localization with respect to time for the given stimulus (liked and disliked music) in various EEG bands was established by implementing a multi-resolution analysis algorithm using Wavelet Packet Decomposition (WPD).Ten healthy adults with an average age of 20 years (without any formal training in music) participated in this study. The perceived emotion of the participants was assessed using Self-Assessment Manikin (SAM) scale and brain activity,while they were listening to music,was recorded using EEG. A high frontal asymmetry index score was noted at mid-frontal (F3 and F4) and lateral frontal (F7 and F8) electrode locations indicating positive emotion. The result suggests that playing the disliked music elicits neither negative emotion nor positive emotion as the changes were noted only at lateral frontal (F4 and F3). Apart from these, there was an increase in the theta band energy of the frontal midline only for liked music and increased beta component energy was observed only at frontal electrode locations while listening to disliked music. The participants' perceived emotion (valence/arousal) matched with induced emotion for liked music whereas for disliked music only the arousal component was similar.

1. Introduction

Most of us listen to the music of our choice while performing our day to day activities as it exposes us to different emotional states. Music-induced emotions have been extensively studied by many researchers [1–4] and it is considered to be the strongest stimulus to induce emotion. Music has the ability to enhance or weaken listener's emotion [5,6]. Music is shown to alter or evoke emotions [2] with subjectively pleasant music stimulus leading to positive emotions. While unpleasant melodies lead to negative emotions, these changes were also reflected clearly in the physiological systems of the human body. Music fulfilment is highly subjective and varies across cultures [7]. The listeners perceive the emotion better if the music is familiar and belongs to their individual culture [8–10]. Wong et al. [11] investigated bimusicalism and musical culture between Americans and Indians. In their study, American participants rated Indian music as tenser whereas Indian participants rated western music as tenser. Listening to music from an unknown culture may lessen the emotional reward compared to listening to native familiar music [12]. Moreover, the stimulus that excites one individual may not have any effect on another [5,13,14]. Blood and Zatore [1] used participant-selected music in their research to produce a more reliable and intense emotional response. Familiar musical pieces self-selected by participants' augmented intense emotional experiences more than unfamiliar pieces [15]. Based on the previous researchers' findings, in the current study, the participants were asked to bring their choice of familiar music with lyrics in their native language. As emotion is extremely subjective the same music type may not induce similar emotion in two different persons. Hence the subjective choice of liked and the disliked music was allowed instead of experimenter-selected music.

Several researchers in their studies [16–18] concluded more positive valence experiences produced high left frontal lobe activation, whereas more negative valence experiences create high right frontal lobe activation. Sackeim et al. [19] concluded an asymmetry of activity in the frontal lobe due to positive and negative emotions.

* Corresponding author.
E-mail address: adalbiotech@gmail.com (A. Kanagasabai).

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In EEG this is reflected as an asymmetric decrease of left frontal alpha power during positive emotion and decrease of right frontal power during negative emotion [4,17,20,21].

Emotion and motivation associated with the affective stimulus were measured using frontal asymmetry index scores and the elevated activity of the left frontal brain in relation to the relative right frontal brain was associated with positive approach and higher engagement [22,23]. The decreased alpha power at frontal electrode locations reflects more brain activity which implies increased engagement (approach/positive) and lower brain activity means more alpha power which means decreased engagement (withdrawal/negative). The researchers [24–26] concluded that the physiological associations of emotions are possibly found in the Central Nervous System (CNS) instead of relying on peripheral physiological responses as brain signals reflect the direct measure of the induced emotion and these changes can be evaluated using Electroencephalogram (EEG) or functional Magnetic Resonance Imaging (fMRI).

EEG is the electrical pattern recorded on the surface of the brain formed by the aggregate of neural activities from millions of neurons. EEG measures the varying electrical activity caused by a great number of stimulating dipoles formed during neural excitations. And these excitation results in complex patterns of neural activity that varies with respect to time and also after a stimulus is presented [27]. The EEG recordings are classified into bands of frequencies follow: Delta (0–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), and Beta (13–22 Hz) [28]. Each frequency band can be associated with a specific function of the brain [27].

EEG signals are non-linear and highly non-Gaussian signals and play an important role in brain functional analysis. They are highly composite and random in nature [29,30]. Several signal processing have been employed, in particular, the power spectral analysis using Fourier Transform (FT) has been widely used to assess brain activity. It provides the frequency content of signal but fails to provide information about the time localization due to the transient periodicities and non-stationary properties of EEG signals [31,32].

The other choice would be Short Time Fourier Transforms (STFT) which is a time-frequency analysis method. The STFT presumes the stationary of the EEG signal within a temporal window to complement the time-frequency resolution selected for the spectral analysis [31,32]. In STFT, the temporal window is of finite length, then it covers only a portion of the signal, and the choice of the window decides the resolution of signal, if the window is too narrow, the frequency resolution will be poor; and if the window is too wide, the time localization will be less deprived [32–34].

The Wavelet Transform (WT) is a multi-resolution analysis method that gives a more accurate temporal localization. It is a new two-dimensional time-scale processing method for non-stationary signals [35]. Its main advantage is to provide simultaneous information on the frequency and time, the location of the signal characteristics, in terms of the representation of the signal at multiple resolutions that correspond to different time scales [36,37]. In WT, filters of different cut-off frequencies are used to analyze the signal at different scales. Among time–frequency analysis methods, the wavelet transform confines the slight changes in the EEG signals as theses minute deviations are hard to spot using the naked eye in the EEG signals. This transform has the ability to analyze EEG signals at different scales and the minute details of sudden changes and similarities in EEG [38]. This also gives a time-variant decomposition so it is possible to choose different wavelet coefficients for different time ranges [39]. There are two types of wavelet analysis: Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT).

Discrete Wavelet Transform (DWT) decomposes the signal into approximation and detail coefficients and gives the first level of decomposition [38]. The approximation coefficients in every level are further decomposed into the next level of approximation and detail coefficients. The approximation coefficients provide the smoothening to the signal. The features extracted from the detailed coefficients at various levels that represent different frequency bands give the characteristics of the time series and DWT coefficients can be used directly as features. In the discrete case, filters of different cut-off frequencies are used to analyze the signal at different scales. The signal is passed through a series of high-pass filters to analyze the high frequencies, and it is passed through a series of low-pass filters to analyze the low frequencies. The resolution of the signal, which is a measure of the amount of detail information in the signal, is changed by the filtering operations, and the scale is changed by up-sampling and down-sampling operations. A more accurate extraction of the frequency band is required as they vary with respect to time and provides the information about the mental state. Wavelet Packet Decomposition (WPD) can be applied to generate spectral resolution fine enough to meet the problem requirement.

Wavelet Packet Decomposition is the extension of the Wavelet Decomposition (WD) technique. It includes multiple bases with different basis, resulting in different classification performance and covers the shortage of fixed time-frequency decomposition in DWT [40]. Basically, wavelet decomposition splits the original signal into two subspaces namely "V" and "W" that are orthonormal complemented to each other. "V" provides low frequency information about the original signal and "W" provides the high frequency information [41]. In DWT, each level is calculated by passing only the previous wavelet approximation coefficients through discrete-time low- and high-pass quadrature mirror filters [41]. However, in WPD, both the detail and approximation coefficients are decomposed to create the full binary tree [42]. The WPD provides a complete wavelet packet tree and is a family of signals derived from a single mother wavelet. Its associated scaling function can subdivide the distinct scales of wavelet decomposition into subscales. The WPD is generated by a filtering scheme similar to that used in a conventional DWT. The difference between the two techniques is that wavelet packet decomposition helps further splitting of the detail functions into two or more sub-bands. However, due to the down-sampling process, the overall number of coefficients is still the same and hence there is no redundancy.

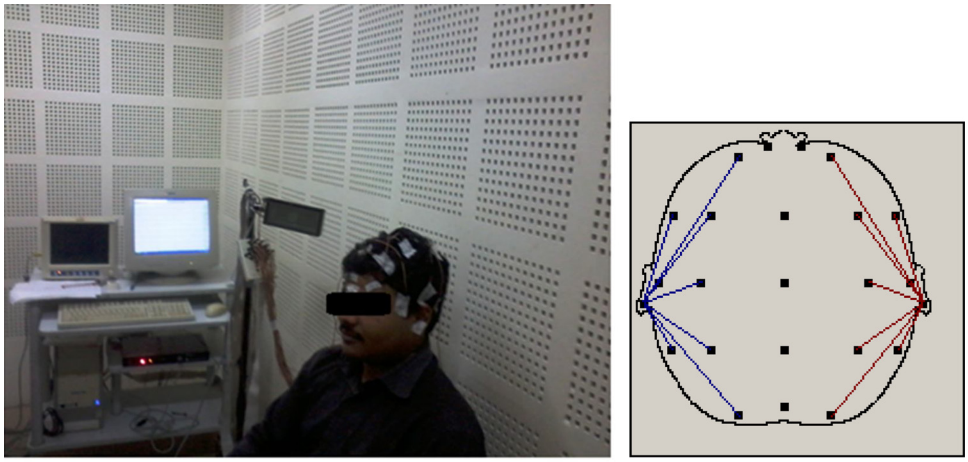
In the present study, wavelet packet decomposition was preferred as it is non-redundant, reduces the computer memory and provides optimal time-frequency localization and smoothness [36,37] as this is needed to evaluate the induced emotional states while listening to music.

Most of the researchers were on the western style of music and western inhabitants [2,43,44]. The current study explores whether participants' choice of liked and disliked music will have an influence on induced and perceived emotion. This study attempted to establish a correlation between induced and perceived emotions. EEG was used to analyze the induced emotion on brain and participants' perceived emotions were measured using self-reported Self-Assessment Manikin (SAM) scale. In this study, feature extraction technique played a major role in analyzing the temporal resolution of the recorded EEG signals. The frequency localization with respect to time for the given stimulus (liked and disliked music) in various EEG bands was established by implementing multi-resolution analysis algorithm.

2. Methods and materials

2.1. Participants

Twelve normal, healthy adults participated in the study. Mini-Mental Test (MMT) [45] was conducted before the commencement



a) b)

Fig. 1. a) Experimental setup includes data acquisition systems for recording electroencephalogram (EEG) signals and b) Monopolar montage used for recording EEG signal.

of the experimental protocol in order to assess and quantify the cognitive function of the participants. The scores of the participants from the MMT were secured between 27 and 30. In the outcome of the MMT, no participants had cognitive impairment which led to their selection for the study. Based on the scoring proposed by Folstein et al. [45], scores of 25–30 out of 30 were considered as normal, 21–24 as mild, 10–20 as moderate, and <10 as severe impairment. Even though twelve participants were recruited for the study, the recorded EEG data for two participants were completely corrupted with noise, hence only the data corresponding to ten participants were analyzed. All experiments were performed at the Biomedical Engineering Division of our Institute. Testing was conducted in the morning in a sound proof room, where the participants were instructed to sit in a comfortable chair. The study was carried out in accordance with the guidelines of the Institutional Ethics Committee of the Institute for Human Volunteer Research. All volunteers signed the informed consent before participating in the study.

2.2. Selection of music

The participants were asked to bring their choice of familiar music with lyrics in their native language. As emotion is a skewed affair, the subjective choices of liked and disliked music were used instead of experimenter-selected music. None of the participants selected identical pieces of music as their choice.

Liked music: All participants selected melody as their choice of liked music, i.e., the melodies played with lyrics in congruent style. The played music that they liked and felt to be pleasant/low arousal, induced positive emotion.

Disliked music: All participants selected upbeat music as their choice of disliked music, i.e., the upbeat music played with lyrics in incongruent style. The played music that they disliked and felt to be unpleasant/high arousal, induced negative emotion.

The duration of each musical stimulus was 180 s (3 min). The music stimuli were played through Windows Media Player, at a comfortable decibel level. It was manually switched on after 3 min of a baseline period (silence), and switched off after 3 min (presentation of the musical stimuli). The participants' order of involvement in the study (liked versus disliked) was randomly decided based on the tossing of an unbiased coin. In order to reduce the possibility of cross-condition contamination, a gap of one week was maintained; participants listened to the second category only after taking a week's time since they listened to the first category.

Table 1
Self-Assessment Manikin (SAM) scale criteria used for evaluating perceived emotional valence and arousal.

Scale	Valence	Arousal
5	Pleasant and Pleased	Aroused
4	Pleasant or Pleased	Wide Awake
3	Neural	Neutral
2	Unsatisfied	Dull
1	Unpleasant	Calm

The choice of the participants on selected music (liked/disliked) was considered as an important factor to induce emotion.

2.3. Participant rating

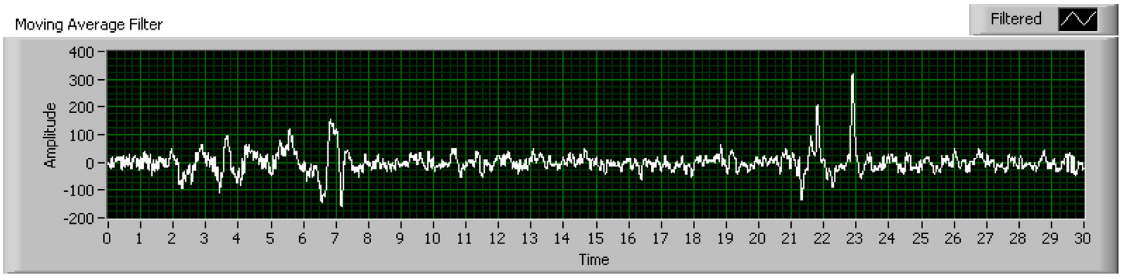
The Self-Assessment Manikin (SAM) scale is economical and easily measures the personal response to an affective stimulus [46]. SAM scale is a non-verbal five pointer scale that measures the valence (pleasant/unpleasant) and arousal (excited/calm) [47]. It was used in the study to assess the affective reaction to the participants' selected liked/disliked music. The participants were asked to rate their perceived feeling after listening to the selected music. Only the valence and arousal representations were considered for this study. The scoring for the subjective measures were calculated based on the information provided in Table 1.

2.4. Experimental protocol

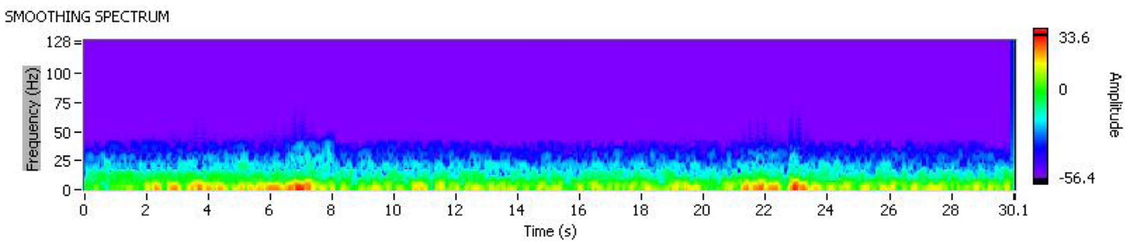
Experiment duration was confined to 10 min, which consisted of 30 s eyes-open and 30 s eyes-closed periods, 3 min of baseline, 3 min of listening to music, and 3 min of resting period after listening to music. The baseline and rest were considered as silent period. EEG was recorded during the entire session and on both the experimental days. The music-listening period (liked/disliked) was assigned as Condition 1 and the rest period as Condition 2. The participants were asked to keep the eyes open for both the conditions.

2.5. Electrode placement

Silver-Silver Chloride (Ag/AgCl) electrodes were used to avoid potential shifts due to electrode polarization. To ensure adequate contact impedance between the electrodes and the scalp, the par-



(a)



(b)

Fig. 2. (a) Moving average filtered output of the raw EEG signal with non-removal of eye blink and (b) Time–frequency representation of the moving average filtered output (Epoch of 30 s).

Table 2
Different mother wavelet used for denoising and their corresponding Signal-to-Noise Ratio (SNR) values.

Type of Mother Wavelet	Signal to Noise Ratio (dB)
Symlet (Sym 3)	46.28
Coiflet (Coif 3)	48.64
Daubechies (db4)	51.37
Daubechies (db9)	48.16
Daubechies (db12)	44.60
Daubechies (db2)	31.43
Bio-orthogonal (bior3_3)	31.90
Haar	9.55

ticipants were asked to wash their hair prior to arrival, and the scalp was cleaned with white spirit. EEG conductive paste was used to improve potential conduction, and the impedance was kept below 5 kΩ between the electrode and the scalp.

Active electrodes were placed in a 10–20 International standard electrode placement system on all cortical lobes such as frontal (Fp1, F3, F7, Fz, Fp2, F4 and F8), temporal (T3, T5, T4 and T6), parietal (P3, Pz and P4), occipital(O1 and O2) and central (C3, Cz and C4) (Fig. 1).

In the present study, monopolar montage was selected which picked up the voltage difference between an active electrode on the scalp and a reference electrode A1 and A2. The reference electrodes were arranged in linked ears. The left hemisphere active electrodes were Fp1, F3, F7, T3, T5, O1, P3 and C3 with a reference electrode A1. The right hemisphere active electrodes were Fp2, F4, F8, T4, T6, O2, P4 and C4 with a reference electrode A2. The difference in potential between the active site and reference site was measured.

EEG signals were recorded using RMS EEG-32 Super Spec device (RMS, India) with a sampling frequency of 256 Hz/channel. Raw EEG signals were filtered using an in-built low-pass filter with user-defined cut-off frequencies of 15 Hz, 35 Hz and 70 Hz, from which 70 Hz was selected for the recording and high-pass filter with user-defined cut-off frequencies of DC,0.1 Hz, 0.3 Hz, 0.5 Hz, 1.0 Hz, 3.0 Hz, 5.0 Hz, from which 0.1 Hz was selected. Hence, the raw EEG signals were filtered using a low- and high-pass filter with cut-off frequencies of 0.1–70 Hz and the power-line interference noise (50 Hz) was eliminated using a notch filter. The sensitivity was set to 7.5 μV and the sweep was set to 30 mm/sec. The recorded EEG signals are usually contaminated by muscle artifacts and sometimes they are wrongly taken as high frequency neuronal activity as the spectral bandwidth of muscle activity falls between 20 Hz–300 Hz [48]. Hence, removal of artifacts becomes primary important as they overlap with neuronal activity. In this study, the in-built muscle rejection (EMG ON) with 30 Hz double pole software filter was selected. This in-built filter provides the low noise level profile <0.3 μVRMS and also attenuates the frequency above 30 Hz thereby provides better artifacts removal.

2.6. *Data processing*

2.6.1. *Pre-processing*

The statistical characteristics of the raw EEG signal changed over the time and the signal was corrupted with random noise. Hence, the recorded EEG signals for various experimental conditions were pre-processed by using a moving average filter with a rectangular window of half-width 3 ($N = 1 + 2M$ samples where $M = 1$).This uses M input points and computes the average of those M-points and produces a smoothened output. The raw signal of 30 s epoch corrupted with noise was band limited to 0.2–45 Hz using Chebyshev band-pass filter of order 8, with a pass band edge frequency of 0.2 Hz–100 Hz, stop band edge frequency of 0.1–101 Hz, pass band ripple of 1 dB, and stop band attenuation of 20 dB. Fig. 2 shows the moving average filtered output of the raw EEG signal and the time–frequency representation of the moving average filtered output where the signal is band limited. The moving average filter reduced the power-line interference but the eye blink was not removed.

2.6.2. *Wavelet denoising*

The eye blink and movement of eyeballs are collectively called as ocular artifacts and these artifacts sometimes dominate the actual signal and mask the significance of brain activity. The effective removal of ocular artifacts was achieved using wavelet denoising techniques based on thresholding. As wavelet based denoising

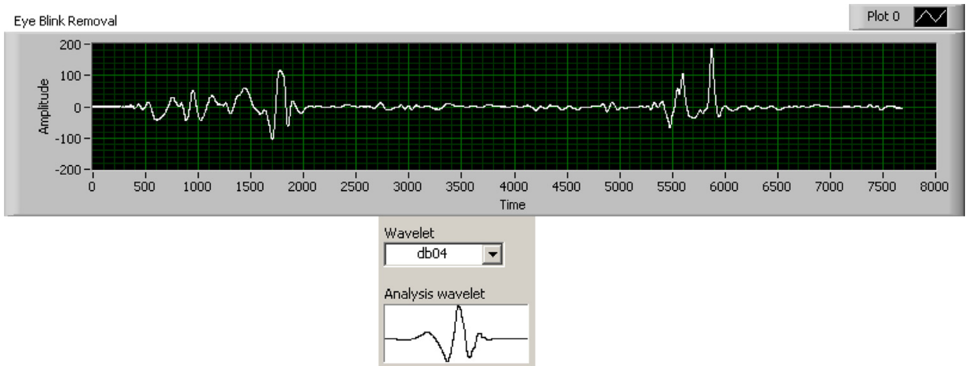


Fig. 3. Eyeblink extracted from the moving average filtered EEG signal (Epoch of 30 s).

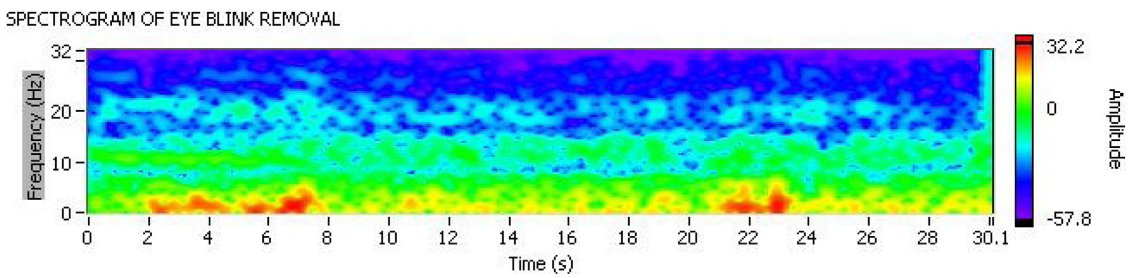


Fig. 4. The Time–Frequency Representation of eye blink removal at level 6 (Epoch of 30 s).

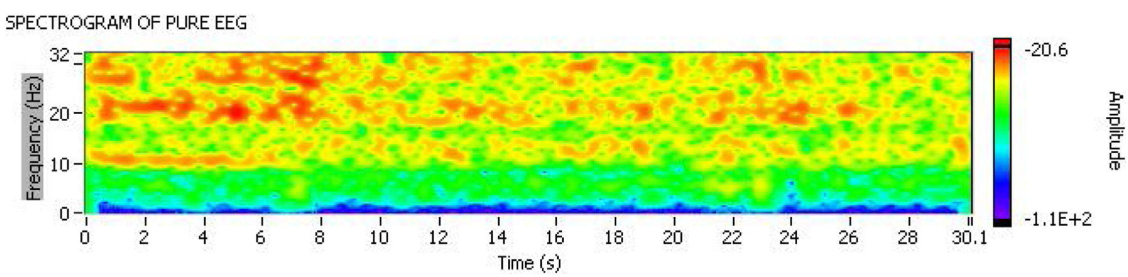


Fig. 5. shows the Time – frequency representation of wavelet packet coefficients of pure EEG signal.

Table 3
Frequency ranges of EEG band and their corresponding approximate (A) and detailed (D) coefficients extracted from Wavelet Packet Decomposition (WPD).

EEG Band	Frequency Range	Wavelet Packet Decomposition Coefficient
Total bandwidth of EEG signal	0–32 Hz	A (3, 1)
Theta band	4–8 Hz	D (6, 1)
Alpha band	8–12 Hz	A (6, 2)
Beta band	16–32 Hz	D (4, 1)
Delta band	0.1–4 Hz	A (6, 1)

method provides the best performance for removing the ocular artifacts as they do not depend on the reference Electrooculogram (EOG) or visual scrutiny. Krishnaveni et al. [49] stated that the adaptive algorithm based on SURE (Stein's Unbiased Risk Estimate) gives an enhanced outcome of denoising EEG signals that are corrupted with ocular artifacts when compared with the non-adaptive algorithm. Apart from that the selection of appropriate mother wavelet and a number of decomposition levels, it depends on the recurrent pattern of the signal and the dominant frequency components of the signal [50,51]. In addition to that, the quality of the corrected signals depends strongly on the quality of the isolated artifact (eye blink).

The effectiveness of the denoising analysis lies in the fact that estimation was done by calculating the Single-to-Noise Ratio (SNR). The SNR is defined as the ratio of signal power (meaning full information – pure EEG without eye blink) to the noise power (unwanted signal – eye blink) contained in the recorded signal. This denotes the quality of the signal that is used to select the most efficient mother wavelet for denoising for extracting the EEG features from the recorded signal. Out of various mother wavelets shown in Table 2, Daubechies (db4) was selected as a mother wavelet since it had high SNR value (51.37 dB).

In this study, db4 mother wavelet with decomposition level of 6 was used to remove the eye blink and in the threshold settings, SURE thresholding rule was selected with multiple levels rescaling method. The selected mother wavelet should perform both denoising and decomposition remaining compatible for all the recorded EEG channels [51]. Figs. 3 and 4 and shows the eye blink extracted from the moving average filtered EEG signal and its time-frequency representation using db04 at level 6 respectively. Fig. 5 shows the time frequency representation of pure EEG signal used for feature extraction.

2.6.3. Feature extraction and wavelet packet component energy

The offline analysis of various conditions (music-listening and rest) was performed using wavelet packet decomposition. The

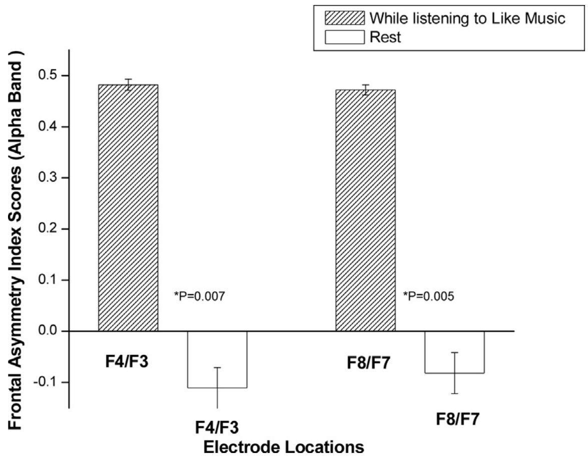


Fig. 6. Mean and one-standard error of frontal asymmetry index scores while listening to liked music and during rest period.

decomposition was then applied to both the approximation and detail coefficients, which are denoted by A and D respectively. The wavelet packet node number for approximation (A) and detail (D) coefficients are denoted as A (m, n) and D (m, n), where m is a decomposition level and n is a node number. The decomposition levels for each frequency band of EEG are given in Table 3.

The wavelet packet decomposition was used to extract the alpha, beta, and theta bands. The representation of a signal by the means of wavelet packet node energy is more robust than using wavelet packet coefficients directly as this gives energy stored in the component signal [34,52]. The total energy E(k) contented of the signal can be decomposed into a sum of wavelet packet coefficients that correspond to different frequency bands (Eq. (1)).

$$E(k) = \sum_{j=-N}^{-1} |C_j(k)|^2 \tag{1}$$

Where $C_j(k)$ represents wavelet coefficients and energy at each resolution level j (1 to −N) depicts the energy of the detail signal. The relative wavelet energy provides information associated with the different frequency bands present in the EEG that can be used as features to the classifiers [33,52]. The relative wavelet packet nodal energies (p_j) at alpha, beta and theta were calculated using the formula given in Eq. 2 for various experimental conditions (while listening to music and during rest), across all the 19 electrode location.

The relative wavelet component energy=

$$p_j = \frac{E_j}{E_{tot}} \tag{2}$$

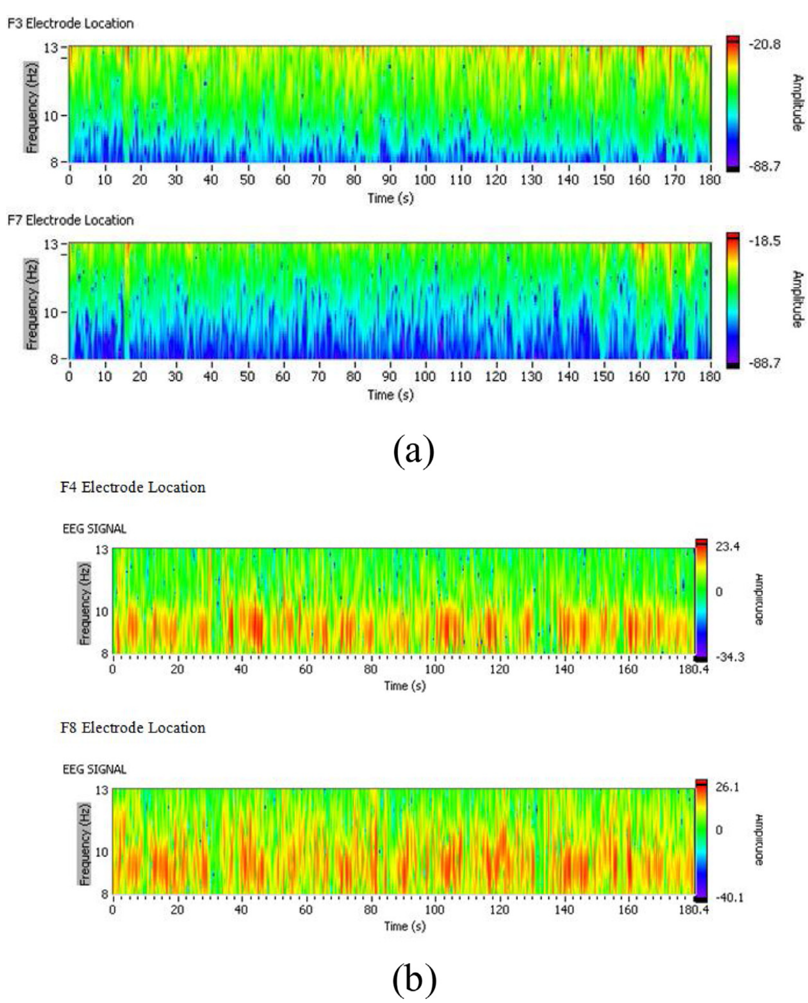


Fig. 7. Time–frequency representation of wavelet packet coefficient at the alpha band while listening to liked music. (a) Relative alpha component energy at left frontal electrode locations (F3 and F7) and (b) Relative alpha component energy at right frontal electrode locations (F4 and F8).

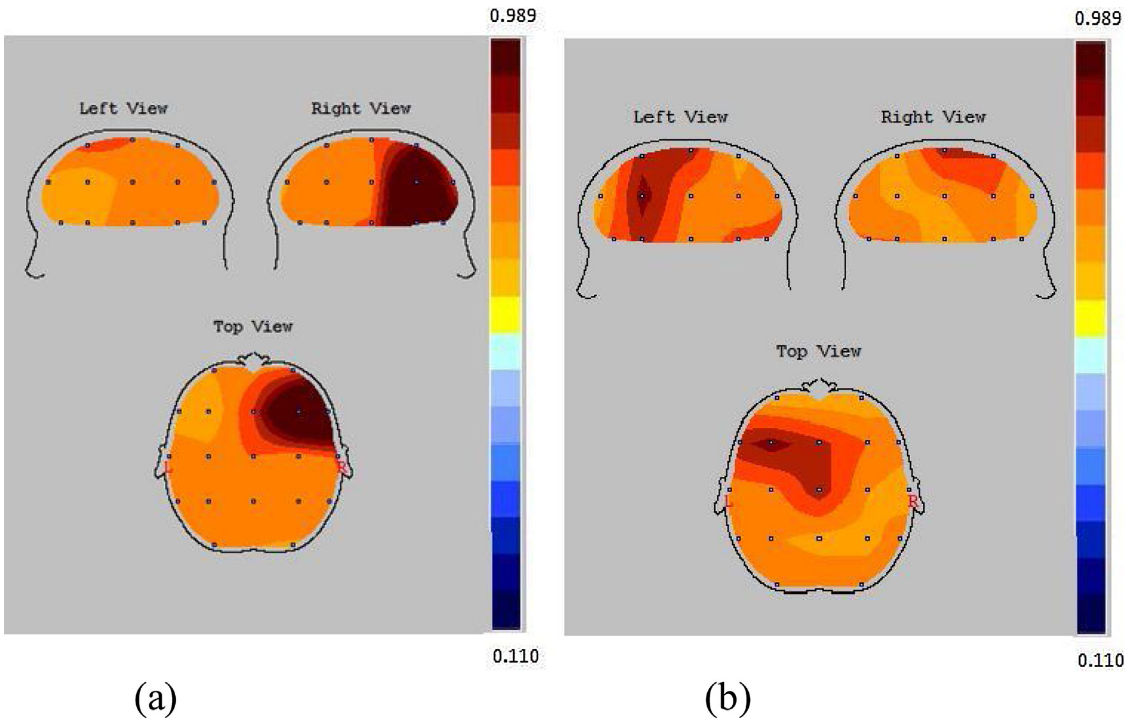


Fig. 8. Averaged topography maps of changes in relative alpha component energy. (a) while listening to liked music and (b) during rest condition. Color bar at the right-hand side represents magnitude of the component energy level.

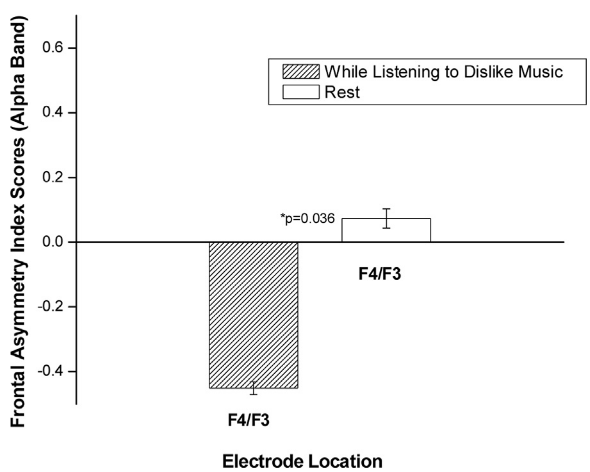


Fig. 9. Mean and one-standard error of frontal asymmetry index scores while listening to disliked music and during rest (silence).

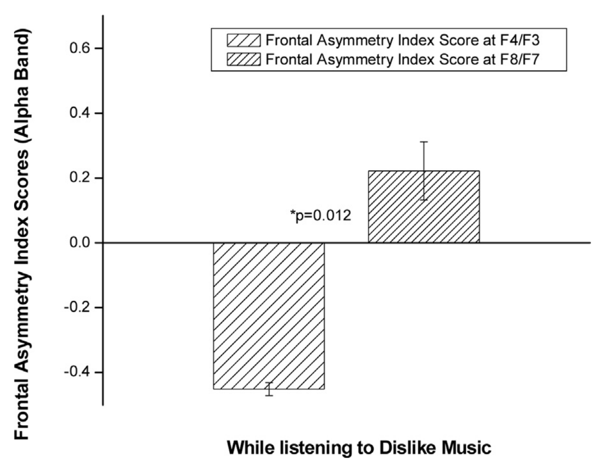


Fig. 10. The Mean and one-standard error of frontal asymmetry index scores at the mid-frontal (F3 and F4) and the lateral frontal (F7 and F8) electrode locations.

Where E_j is the wavelet packet nodal energy of that particular band and E_{tot} is the total wavelet component energy which corresponds to entire spectrum (0–32 Hz) of EEG signal.

The entire analysis was performed by using Wavelet Analysis Tool Kit in LabVIEW® 2014. The brain topographic mapping for relative component energies intended for alpha, beta and theta band against each location was achieved using customised brain mapping software provided by RMS analysis software.

2.7. Statistical analysis

The measured parameters were not normally distributed. Hence, the Friedman test, a non-parametric substitute to the one-way ANOVA with repeated measures, was selected to measure whether there are overall differences between the measured parameters (relative alpha, beta, and theta component energies) at three different conditions (silence, listening to liked music, and disliked music) at 19electrode locations (F3, F7, F8, F4, T3, T4, T5, T6, C3, C4, P3, P4, Cz, Fz, and Pz). The same participants listened to the liked and disliked music on two different days so that the effect of induced emotion owing to one music will not affect the other. The set alpha value was $p = 0.05$. The post-hoc Wilcox on signed ranks was performed on different combinations of related groups and Bonferroni adjustment was calculated. The alpha value was divided by three conditions ($0.05/3 = 0.017$). Consequently, the new significant level was set at $p = 0.017$. The participants' choices of liked, disliked music and no music (silence) were considered as independent variables. The induced emotion on brain signals were measured using EEG, and measured relative component energies in alpha, beta, and theta bands were considered as dependent variables. The perceived emotion was measured using SAM scale ratings for valence and arousal. These subjective rat-

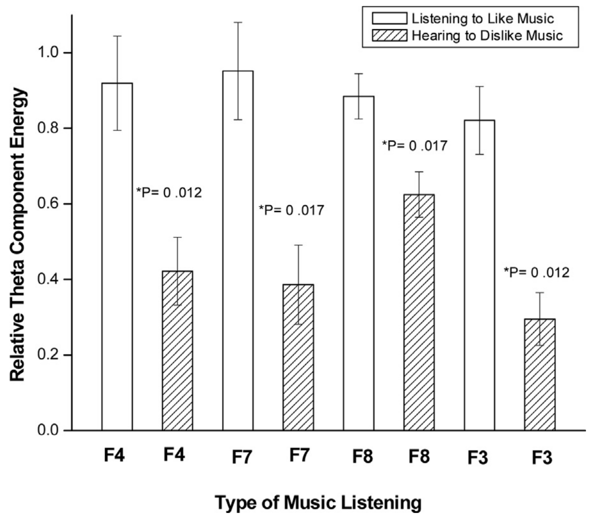
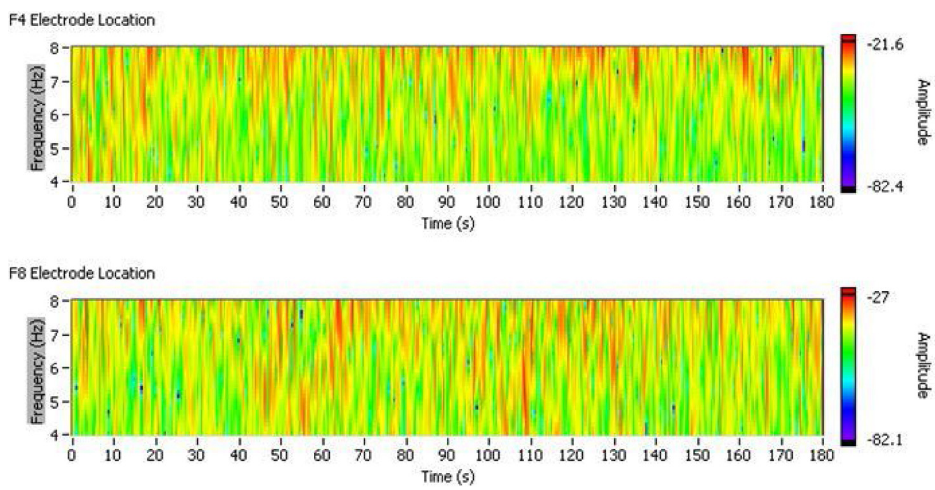


Fig. 11. Mean and one-standard error values of relative theta energy on F3, F4, F7 and F8 frontal locations of the brain while listening to liked music when compared with disliked music.

ings have also been considered as dependent variables. The analysis was performed using IBM SPSS Statistics for Windows, Version 20.0 (Armonk, NY: IBM Corp).

3. Results

The mean relative alpha, beta, and theta component energies were calculated for the left and right hemisphere electrode locations during all the experimental conditions (while listening to liked and disliked music, and during silence). The relative alpha component energies were compared between the right and left hemispheres to gauge the induced emotion of the played music which gives the measure of positive or negative emotion. The relative theta component energies at frontal electrode locations give the measure of valence (pleasant/unpleasant). The arousal was calculated by measuring the relative beta component energy (low/high). The perceived emotion was measured using subjective rating by SAM scale and the results of perceived and induced emotions were compared.



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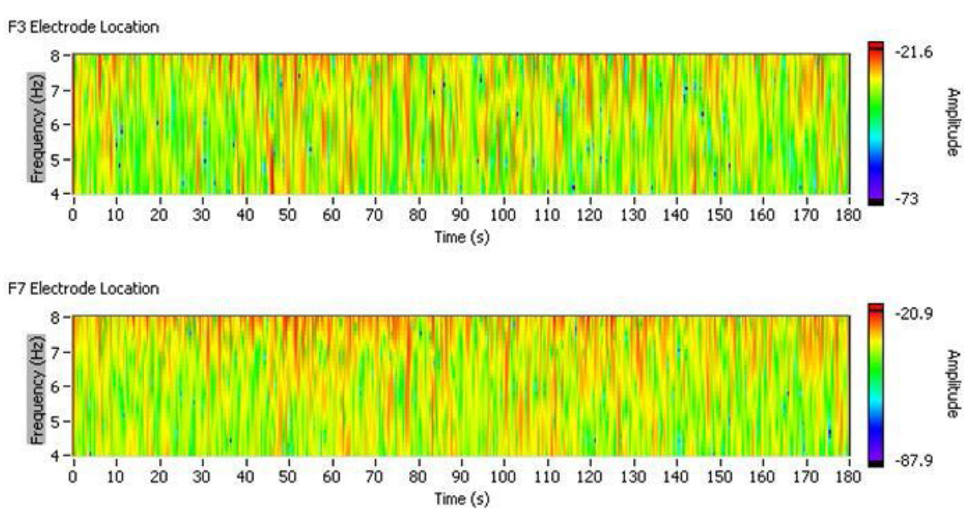


(b)

Fig. 12. Time–frequency representation of wavelet packet coefficient in theta band (a) at right frontal electrode locations (F4 and F8) while listening to like music and (b) at left frontal electrode locations (F3 and F7).

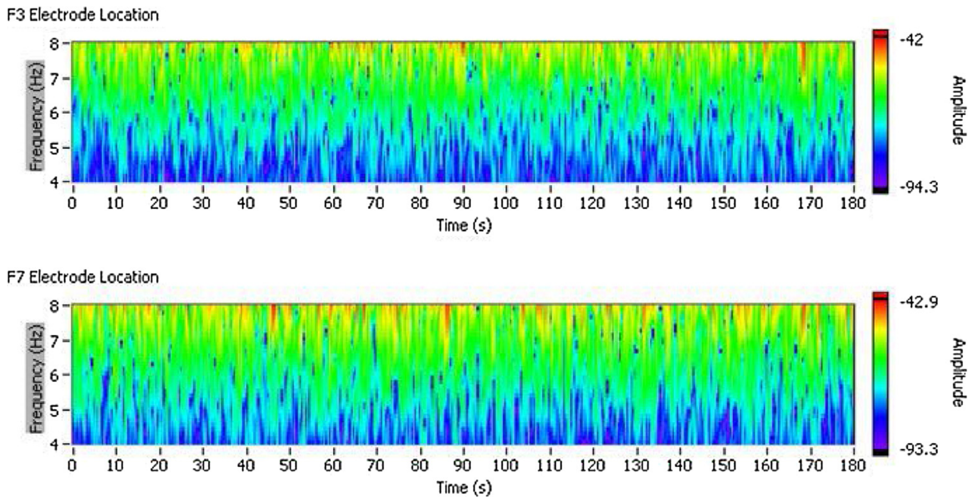


Fig. 13. Time–frequency representation of wavelet packet coefficient at theta band at left frontal electrode locations (F3 and F7) during Rest.

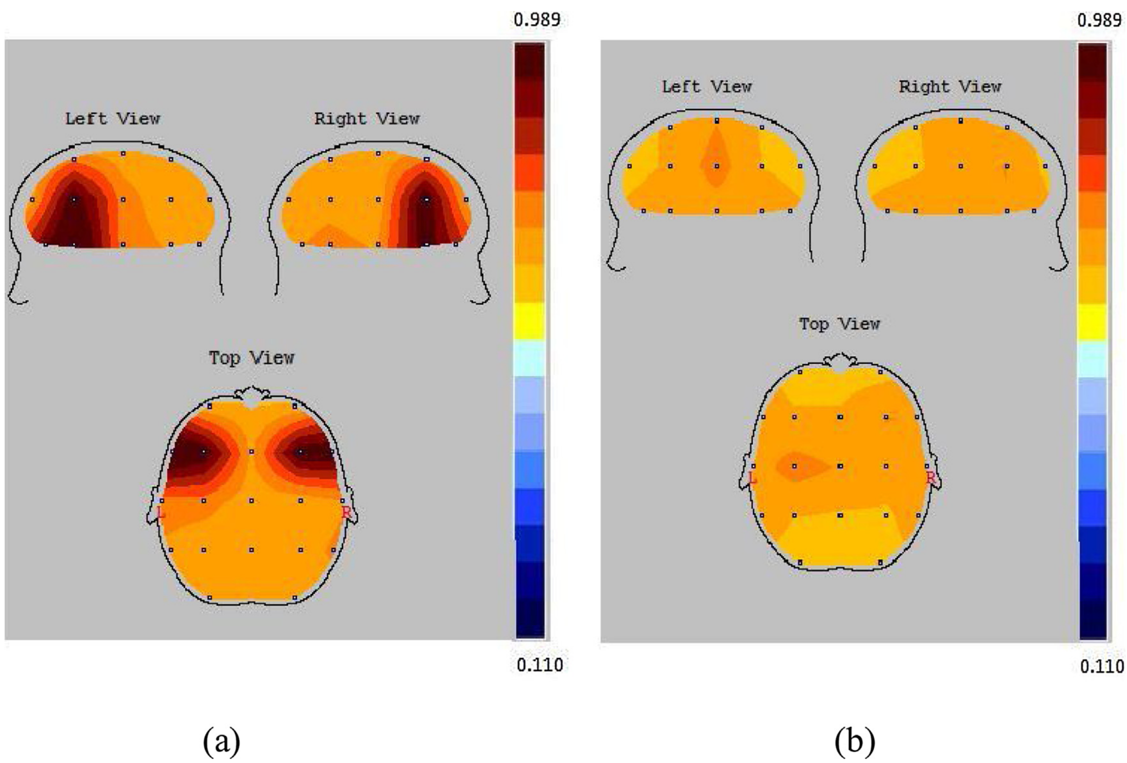


Fig. 14. (a) Averaged topography maps of changes in relative theta component energy against of each electrode while listening to liked music, (b) Averaged topography maps of changes in relative theta component energy against of each electrode during rest (Color bar at the right-hand side represents the component energy level).

The Friedman test was computed and a statistically significant difference was noted in the measured parameters (relative alpha, beta and theta component energies) depending on which type of music was listened to, $\chi 2$ (134) = 321.33; p = 0.0001.

3.1. Analysis of alpha component energy

The relative alpha component energy was significantly high while listening to liked music at F4 (Z = −2.380, p = 0.017) and F8 (Z = −2.521, p = 0.012) compared with silence (rest), and was noted only at these locations. Apart from that, the relative alpha component energy was significantly low at the left frontal electrode locations F3 when compared with the right frontal electrode location F4 (Z = −2.521, p = 0.012) and this was also noted at F7 and F8 (Z = −2.380, p = 0.017) while listening to liked music. The frontal asymmetry index was calculated using the following formula: Log [alpha component energy at right frontal electrodes (F4)] – Log [alpha component energy at left frontal electrodes (F3)]. Similarly, it was calculated for F8 and F7 while listening to liked/disliked music. The highest scores for frontal asymmetry were noted while listening to liked music when compared with the rest (silence). Fig. 6 shows that the frontal asymmetry index scores were significantly high at (F4/F3) while listening to liked music (Z = −2.701b, p = 0.007) when compared to rest (silence) and also at (F8/F7) while listening to liked music (Z = −2.803b, p = 0.005) when compared to rest period.

Fig. 7 shows the time-frequency plot of relative alpha component energy at left frontal locations (F3 and F7) and at right frontal

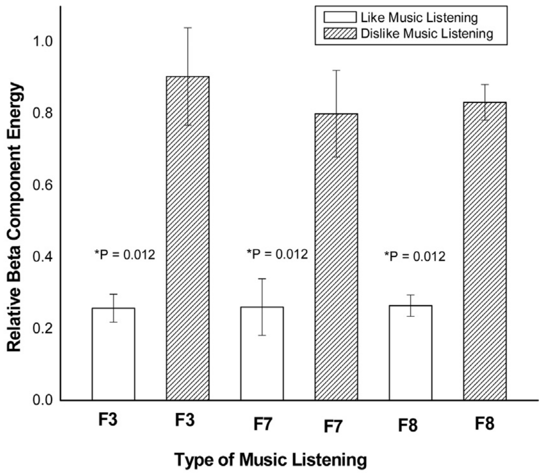


Fig. 15. Mean and one-standard error values of relative beta energy on F3, F7 and F8 frontal locations of the brain while listening to disliked music as compared with being at rest condition.

locations (F4 and F8) respectively. Fig. 8 shows the relative alpha component energy and corresponding brain topographic mappings against each electrode while listening to liked music and rest condition. The elevated activity of the left frontal brain in relation to the right frontal brain is associated with positive approach and higher engagement. There was an asymmetric decrease in relative mean alpha component energy at the left frontal electrodes. This clearly indicates that the liked music induced positive emotion among the listeners. Moreover, the changes were noted only during the musical stimuli administration.

When listening to disliked music, the relative alpha component energy was significantlyhigh ($Z = -2.380$, $p = 0.017$) only at left frontal electrode location (F3) when compared with right frontal electrode location (F4). Even though the relative alpha component energy while listening to disliked music was high at F7 ($p = 0.025$) but it was not significantly found.

The frontal asymmetry index scores (Fig. 9) was significantly low at F4 and F3 locations while listening to disliked music ($Z = -2.100$b, $p = 0.036$) when compared to rest (silence), but this was not notedat F8 and F7 locations while listening to disliked music and rest ($p = 0.779$). This results in low frontal asymmetry score at F4 and F3 locations and high at F8 and F7. The low brain activity is characterizedby more alpha power which in turn means decreased engagement (withdrawal/negative).

There was no asymmetric decrease in relative alpha component energy at lateral frontal electrodes when compared to mid-frontal electrodes (Fig. 10). This suggests that playing the disliked music elicited neither negative nor positive emotion.

3.2. Analysis of theta component energy

The mean relative theta component energy was calculated for all the electrode locations while listening to both liked/disliked music and during the rest period as this gives the measure of the pleasantness of the played music.

The relative theta component energy was significantly high while listening to liked music compared to rest at F4 ($Z = -2.380$, $p = 0.017$), F3 ($Z = -2.380$, $p = 0.017$), F7 ($Z = -2.380$, $p = 0.012$), and F8 ($Z = -2.380$, $p = 0.017$) locations. Interestingly this was noted only at the frontal electrode locations. There was no significant increase in relative theta component energy at other electrode locations (P3, T3, T5, and C3, P4, T4, T6, and C4). At the same time, the relative theta component energy was significantly low while listening to disliked music when compared to rest at F4 ($p = 0.013$), F3 ($p = 0.017$), F7 ($p = 0.012$), and F8 ($p = 0.013$). Fig. 11 shows that the relative theta component energy was significantly high while listening to liked music as compared with disliked music at F4 ($Z = -2.521$, $p = 0.012$), F3 ($Z = -2.521$, $p = 0.012$), F7 ($Z = -2.380$, $p = 0.017$) and F8 ($Z = -2.380$, $p = 0.012$). Figs. 12 and 13 shows the time frequency representation of relative theta component energy

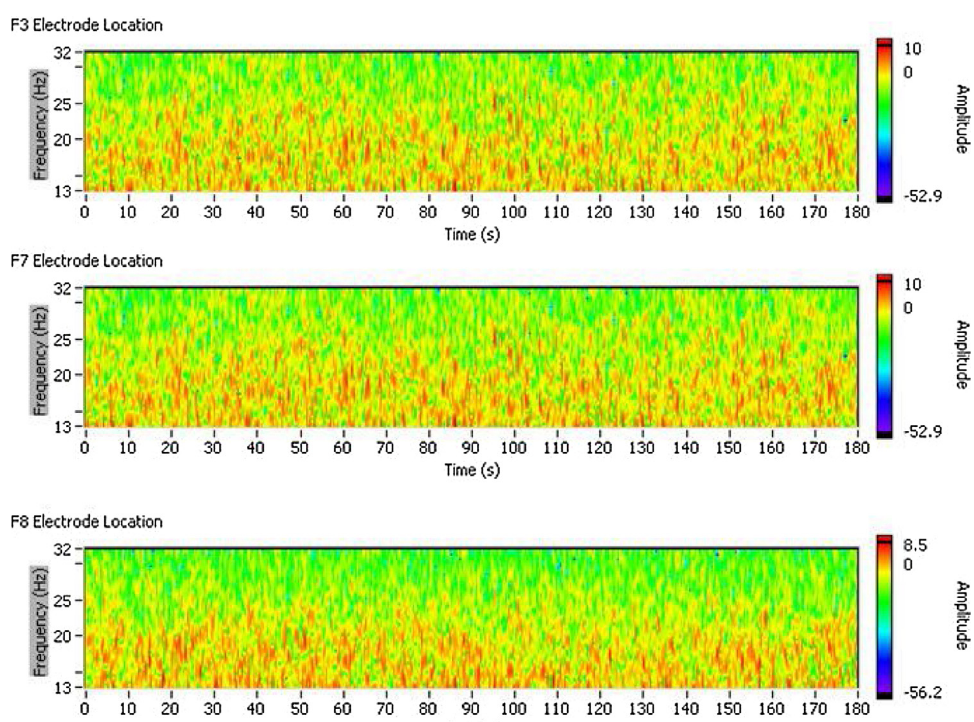


Fig. 16. Time–frequency representation of wavelet packet coefficient at the beta component at frontal electrode locations (F3, F7 and F8) while listening to dislike music.

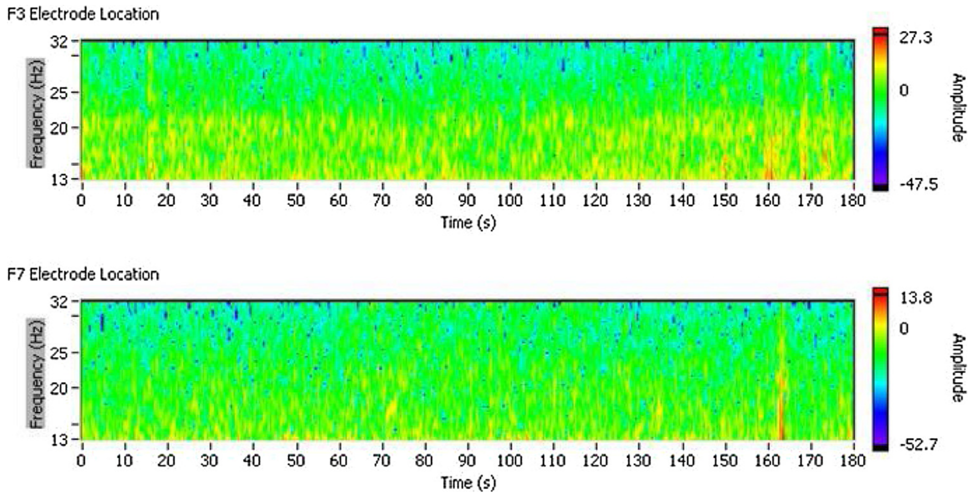
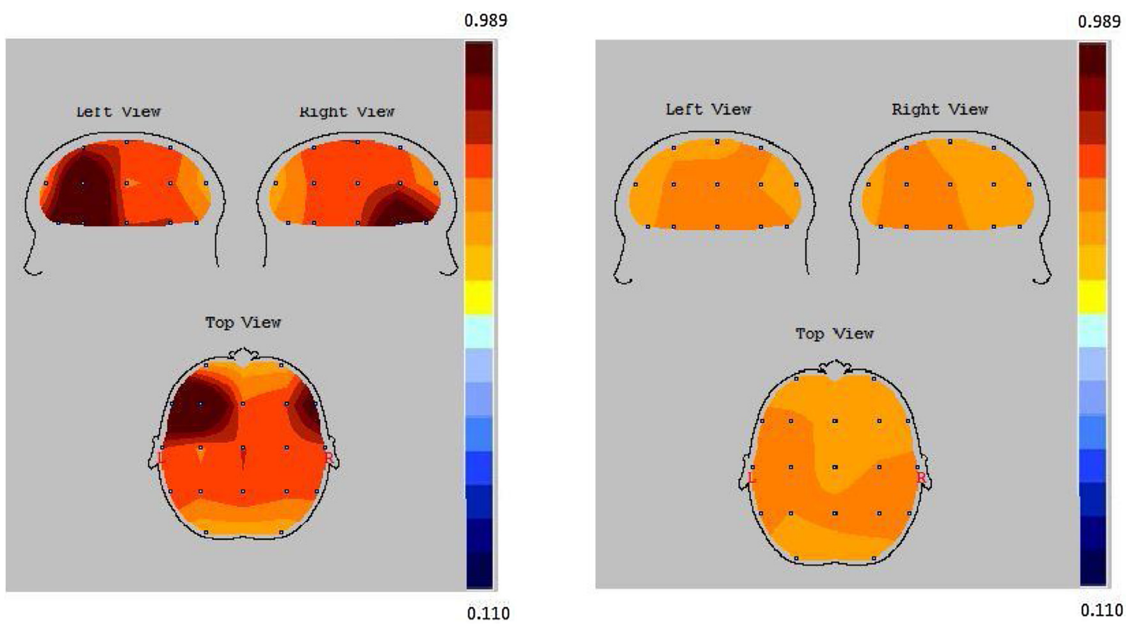


Fig. 17. Time–frequency representation of wavelet packet coefficient at the beta component at frontal electrode locations (F3 and F7) while listening to like music.



(a) (b)

Fig. 18. (a) Averaged topography maps of changes in relative beta component energy against of each electrode while hearing dislike music, (b) Averaged topography maps of changes in relative beta component energy against of each electrode while listening to music (Color bar at the right-hand side represents the component energy level).

against each electrode while listening to liked music and rest condition respectively.

The theta component energy at frontal electrode was stated as midline frontal (Fm) theta and it was high throughout while listening to liked music when compared with listening to disliked music (Fig. 14). This indicates that the played liked music induced pleasantness in the listeners and the disliked music was unpleasant or did not evoke negative emotion.

3.3. Analysis of beta component energy

When comparing the relative beta component, while listening to liked music and disliked music. The relative beta component energy while listening to disliked music was significantly highas compared to listening to liked music at F3 ($Z = -2.521$, $p = 0.012$), F7 ($Z = -2.521$, $p = 0.012$) and F8 ($Z = -2.521$, $p = 0.012$) (Fig. 15). There were no significant changes in relative beta component energy at any electrode locations including at F4 location. This evidently signifies the played dislike music induced arousal.

Overall, the heightened beta frequency in the frontal lobe locations (F3, F7, and F8) indicates that playing disliked music was capable of creating arousal. The relative mean beta component energies were the same for baseline and rest conditions. Moreover, there was no increase in the relative theta component at frontal electrode locations while listening to the disliked music when compared with baseline and the rest, which suggests that the played music was not pleasant (unpleasant and generated high arousal). Fig. 16 shows the extracted beta band wavelet coefficients while hearing disliked music and Fig. 17 shows the extracted beta band wavelet coefficients while listening to liked music. Fig. 18 shows the relative beta component energy and corresponding brain topographic mappings against each electrode while hearing disliked music and like music respectively.

3.4. Comparison analysis

When comparing three different parameters' (relative alpha, beta, and theta) component energies at different electrode locations in three different conditions (silence, listening to liked music and disliked music), significant changes were noted only at F4 and F8 electrode locations for relative alpha and beta band component energies. At F4 ($Z = -2.521$, $p = 0.012$) and F8 ($Z = -2.521$, $p = 0.012$) electrode locations, while listening to liked music, the alpha component energy increased significantly when compared to beta component energy. At F8 electrode location, while listening to disliked music, the beta component energy ($Z = -2.380$, $p = 0.017$) increased significantly when compared to alpha component energy. This clearly indicates an inverse relationship between alpha and beta energy. There were no significant changes in relative theta component energy at any electrode location. In the same way, no changes were noted at parietal (P3 and P4), central (C3, CZ and C4) temporal electrode (T3, T4, T5 and T6) locations.

The subjective feelings for played liked and disliked music were measured using the SAM scale on a five point Likert scale to assess the perceived emotion. The valence scoring was significantly different for the liked and disliked music conditions ($Z = -2.490$, $p = 0.013$). This indicates that the liked music played was considered to be pleasant, while the disliked music was confirmed as unpleasant. Similarly, the arousal scoring for liked and disliked music was also significantly different ($Z = -2.444$, $p = 0.015$) which indicates that the liked music played can be calming and the disliked music excited the participants. This concludes that the liked music is associated with high valence and low arousal (calm), and disliked with low valence and high arousal (excited).

4. Discussion

Emotions are precise responses to distinctive incidents encountered even if only for a diminutive period. The stimulus that excites one individual may not have any effect on another [5,12]. Therefore, selecting a stimulus becomes an important criterion to induce emotion. Based on these findings, in the present study, the participants' preferred liked and disliked Indian music was used to assess the perceived and induced emotions on Indian participants. The perceived emotions of the played music were measured using Self-Assessment Manikin (SAM) scale as it is a cost-effective and easy way to measure the personal response to an affective stimulus [46]. The participants perceived like music as pleasant and low arousal whereas disliked music as unpleasant and high arousal. The induced emotions were measured using EEG as it gives better temporal resolution when compared with fMRI.

In this study, the wavelet packet decomposition is used for EEG data as the wavelet packet coefficients are used for selecting the appropriate thresholding function which helps in denoising the signal. This is followed by reconstruction and the signal after denoising provides better results than wavelet transform [53]. The representation of a signal by the means of wavelet packet node energy is more robust than using wavelet packet coefficients directly as this gives energy stored in the component signal [52,54]. These wavelet packet nodal energies at various EEG bands were used to quantify the induced emotion.

The valence (pleasant/unpleasant) was measured by estimating the theta component energy and the provoked emotions (positive/negative) by calculating the frontal asymmetry index scores and arousal by determining the beta component energy at frontal electrode locations.

The high frontal asymmetry index score indicates approach/motivation behaviour [22–24] which relates to positive emotion. The changes were noted at mid-frontal (F3 and F4) and lateral frontal (F7 and F8) electrode locations while listening to liked music. Whereas the lesser activity in the left frontal electrode location relative to the right frontal electrode is associated with withdrawal/avoidance was noted only at F4 and F3 and not at F8 and F7 locations. This inference suggests that playing the disliked music, neither negative emotion nor positive emotion was elicited as the changes were noted only at the lateral frontal (F4 and F3). Perhaps while selecting the disliked, musical stimuli reminiscent of anger, fear, or sorrow would have elicited negative emotion.

Listening to pleasant music increases the frontal midline (Fm) theta frequencies [4]. The results showed a significant increase in theta component energy at frontal electrode locations F3, F4, F7, and F8 when listening to liked music compared to being in silence and listening to disliked the music. These increases in theta component indicate that the liked music was subjectively pleasing, which supports the findings by Sammler et al. [4]. An increase in beta power was noted in an emotional arousal [4] and frontal increase in beta activity has been shown to correspond to the subjective effect of tension and also as an indicator of cortical arousal taking place in individuals [21,55,56]. The results corroborate their findings that the beta component energy was significantly high only at the frontal electrode locations F3, F7 and F8 while listening to disliked music when compared to liked music. This heightening of beta component energy at the frontal lobe locations (F3, F7, and F8) indicates that the disliked music induced cortical arousal and strain among the participants. These results support the claim that the disliked music induced high arousal.

The results also support the findings of Sulaiman et al. [57] where the alpha and beta waves have been shown to be inversely related when encountering a stressor, with alpha bands decreasing and beta bands increasing in energy this was noted at F4 and F8 electrode locations, the beta component energy was significantly low when compared to alpha component energy while listening to the liked music, whereas while listening to disliked music, this was noted only at F8 electrode location. The relative alpha, beta, and theta component energies remain same for rest conditions throughout the experiment for both liked and disliked music. The changes were noted only while listening to liked and disliked music.

This study encountered a limitation on epoch selection. In the present work, the entire epoch (180 s) that represents music-listening and rest were taken for analysis. Instead of 180 s, epochs were split into 30 s would provide insight realization of time varying characteristics of different EEG rhythm (alpha, beta, and theta) for the experimental conditions. Calculating the relative component energy at various EEG bands for each 30 s epoch would provide the dominant band. This will point to the changes in the valence (pleasant/unpleasant) and arousal of the played music.

5. Conclusion

The perceived and induced emotions of participants selected liked and disliked music were measured using SAM scale and brain activity using EEG. The time varying characteristics of EEG for various experimental conditions were measured using wavelet packet decomposition. Eye blink removal and extraction of different frequency bands of EEG signals were accomplished using mother wavelet db4 as it provided better SNR when compared with other mother wavelets. The high frontal asymmetry index score indicates approach/motivationbehavior which relates to positive emotion and this change were noted at mid-frontal (F3 and F4) and lateral frontal (F7 and F8) electrode locations while listening to liked music. Perhaps selecting disliked musical stimuli reminiscent of anger, fear, or sorrow would have elicited negative emotion. In case of liked music, an increase in frontal theta component, while listening to liked music indicates that the music was considered pleasant. But this effect was not observed while listening to disliked music, confirming that it is an unpleasant stimulus. The increase in the frontal beta component energy was observed while listening to disliked music, which indicates the disliked music induced arousal. The present study concludes that the participants' selected liked music was pleasant and induced positive emotion with low arousal. This correlates with their perceived emotion, whereas the played disliked music was unpleasant and high arousal. Yet it did not induce negative or positive emotion, even though they were perceived as unpleasant.

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