Biomedical Signal Processing and Control 42 (2018) 115–128

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Music induced emotion using wavelet packet decomposition—An EEG study

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ARTICLE INFO

Article history:
Received 8 March 2017
Received in revised form
18 December 2017
Accepted 27 January 2018

Keywords:
Music
Emotions
Electroencephalography (EEG)
Wavelet packet decomposition (WPD)

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.

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https://doi.org/10.1016/j.bspc.2018.01.015
1746-8094/

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