
Depression diagnosis and management using EEG-based affective brain mapping in real time

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Abstract: Development of affective Brain–Computer Interfaces (BCIs) via Electroencephalogram (EEG) has emerged as a cynosure of research in early diagnosis and effective management of depression. However, conventional BCIs are still lacking in terms of high computational complexity, less accuracy due to Fourier phase suppression and lack of substantial conclusion for depression diagnosis. An automated, EEG-based depression diagnostic and management tool is proposed to overcome these limitations. Channel event-related potentials, cross-coherence and power spectra plots in MATLAB are quantified and studied as an outcome to map real-time, emotion-specific multichannel EEG data set into distinct emotional states. A fast and stable fourth-order statistics-based independent component analysis is incorporated to reject temporal/spatial artefacts. Increases in frontal alpha (8–13 Hz) and delta (0.5–4 Hz) power/coherence are during depressed and normal/relaxed states, respectively. Devotional music (relaxed state) is found to facilitate depression elimination. Results are found to be statistically significant across all subjects with minimal *p*-values. Hence, it has been inferred that the proposed model has the potential to aid early and accurate depression diagnostic and management process.

Keywords: affective brain mapping; BCI; brain–computer interface; depression; early diagnosis; EEG; electroencephalogram; emotions; ERP; event-related potential; real time; spectral power.

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1 Introduction

Psychophysiological analysis of human neural responses via EEG has a significant progressive role in the field of cognitive/affective computing to develop more intuitive and advanced Brain–Computer Interface (BCI) applications such as human emotion measurement and stress and depressive disorder recognition in real time. A psychophysiological procedure triggered by conscious and/or unconscious observation of an object or circumstances, which is often associated with mood, character, personality and disposition, and inspiration, is known as emotion (Picard et al., 2001). By expressing non-verbal cues such as modulation of voice, facial expressions, text and body gestures or orally through emotional vocabulary, emotions can be expressed (Rafael and Sidney, 2010). However, these can be consciously faked. There are certain vital but non-invasive physiological modalities being adopted for human emotion appraisal such as Electromyogram (EMG), human heart electrical activity in terms of Electrocardiogram (ECG), Skin Conductive Resistance (SCR), Blood Volume Pressure (BVP), Heart Rate Variability (HRV), Electrodermal Activity (EDA) and human brain electrical activity (Hosseini, 2011). As retrieving emotional states from correlated neural responses is an effective way of implementing affective BCIs (Schaaff and Schultz, 2009), focus has been on exploring the brain activity correlations with emotions. Neural-driven BCIs involve the use of Electroencephalograph (EEG), Electrocorticography (ECoG), Magnetic Resonance Imaging (MRI) or Functional Magnetic Resonance Imaging (fMRI) to capture brain signals from central nervous system. However, EEG is a preferred clinical research as well as functional tool to monitor emotion-specific brain functionality because of its high temporal resolution, lower cost, non-invasiveness and significant suitability to patients without any exposure to high-intensity magnetic fields/radiations (Sakkalis, 2011; Li et al., 2009; Petrantonakis and Hadjileontiadis, 2011). EEG is effectively employed in the assessment of brain syndromes or disorders, coma, brain tumour as well as long-term hitches with thinking or memory (Kim et al., 2004; Chanel et al., 2006; Chanel et al., 2007) as EEG possesses the potential to map correlated neural activation in terms of its strength and region across distinct scalp regions (Teplan, 2002).

Early and accurate diagnosis of depression is crucial as neural/psychiatric/depressive disorders are posing a serious threat and consequently a negative impact on human health. Depression is a neurological syndrome characterised by certain affective, expressive, behavioural and cognitive reactions such as loss of interest, pessimism, helplessness, feeling of worthlessness, fear, frustration, self-damaging behaviour, etc. Repeated exposure to such depressive feelings can eventually lead towards serious abnormalities in humans such as weak immune system, irregular sleep patterns, muscular/cardiac/weight and hormonal disorders and the most dangerously suicidal thoughts or tendency (Andreassi, 2000; Sorgi, 2002; Luneski et al., 2010). The central nervous system is the very first entity in the biological path that becomes activated during visual/auditory stress from the external world and further acts as a mediator to different body organs (Sherwood, 2010). Therefore, there is a need to develop efficient biomarkers for depression diagnosis from human neural responses via EEG.

Extensive research in the field of affective brain mapping has been published on characterising EEG variations during distinct emotion elicitations using Power Spectral Density (PSD) (Kawasaki et al., 2009; Chanel et al., 2011; Gandhi et al., 2011; Wang et al., 2011; Jatupaiboon et al., 2013), Common Spatial Patterns (CSP) (Li and Lu, 2009; Fattahi et al., 2013), Fast Fourier Transform (FFT) analysis (Yoon and Chung, 2013), entropy analysis (Hosseini, 2011; Khalilzadeh et al., 2010; Srinivasan et al., 2007), Higher Order Crossing (HOC) analysis (Petranonakis and Hadjileontiadis, 2010a; Petranonakis and Hadjileontiadis, 2010b), third-order spectral analysis (Hosseini et al., 2010; Hosseini, 2012) and statistical analysis (Takahashi and Tsukaguchi, 2004; Yuen et al., 2013) techniques. Current research findings reveal that PSD is an established technique for EEG signal analysis in the frequency domain (Dressler et al., 2004). A group of researchers' classified emotions elicited by pictures and music stimuli into happy and unhappy states by extracting power spectral features from a single pair of temporal channel EEG (Jatupaiboon et al., 2013). Further, a set of algorithms was implemented using Discrete Wavelet Transform (DWT) to extract correlated EEG sub-band power for emotion classification (Murugappan et al., 2009a; Murugappan et al., 2010; Ubeyli, 2009). The excitement level variations of depressed subjects were captured by analysing their respective conventional Event-Related Potentials (ERP) in the time domain (Dai and Feng, 2012). This was followed by implementation of multi-domain ERP analysis related to states of depression. It was revealed to possess more emotion discriminating ability from human neural responses using negative facial expressions as compared to only temporal or spectral domain ERP analysis (Cong et al., 2012; Zhao et al., 2013). It had also been reported that EEG Spectral Asymmetry (SA), channel ERPs and EEG cortical activity can be used for characterisation of EEG in depression (Fingelkurts et al., 2006; Hinrikus et al., 2010; Olbrich and Arns, 2013).

A comprehensive amount of affective brain mapping techniques has been developed by extracting and correlating individual set of features. Still prior works exhibit few limitations including less accuracy due to Fourier phase suppression, high computational cost and complexity, inconsistent findings and lack of substantial conclusion in the case of depressive disorder detection and management. Also less attention has been paid towards fusion of different sets of features of EEG to retrieve correlated emotional states, particularly depressive disorders from human neural responses. In all, there is a need to further explore and develop an efficient multi-domain feature extraction technique involving robust signal processing and significant statistical analysis to provide a concrete conclusion about recognition of major depressive disorders from human neural responses via EEG.

An attempt has been made in this research to develop an accurate and robust computer-aided depression diagnostic and management tool by analysing multichannel EEG data using fusion of time domain (ERP), frequency domain [PSD, Amplitude Spectral Density (ASD)] and EEG coherence features. The discriminating ability and significance of the extracted depression-related feature set has been tested by applying the *F*-test in one-way Analysis of Variance (ANOVA). High statistical significance indicates the ability of frontal alpha and delta peak power coherence to be developed as a diagnostic tool for depressive disorder via EEG. An algorithm is further proposed in MATLAB to translate an identified 'depressed state' output into operative control signals for automated depression management application using devotional music.

The rest of the paper is organised as follows. Section 2 contains the block diagram of the analysis carried out and describes the experiment design, EEG acquisition, stimuli used, feature extraction, statistical analysis of features and depression diagnostic model design. Section 3 provides the results obtained from the experiments carried out, followed by their discussion in Section 4 and conclusion of the work in Section 5.

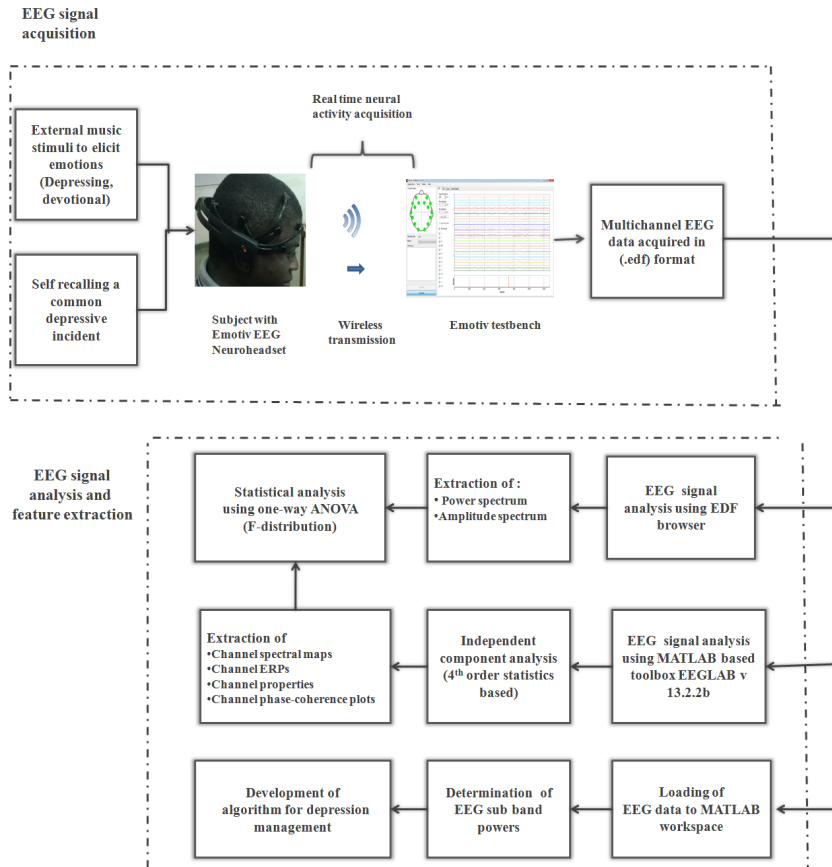
2 Materials and methods

Block diagram of the proposed computer-aided and portable set-up for depression recognition using EEG-based affective brain mapping in real time is shown in Figure 1. It broadly consists of multichannel EEG signal acquisition module to acquire emotion-related brain activities, followed by a signal processing module to analyse acquired emotion-specific EEG data set for extraction of the most discriminating feature set to further develop an algorithm for depression management application. A very preliminary work discussing the detailed design considerations for development of the proposed real-time and portable set-up for emotion recognition using EEG-based affective brain mapping has been reported earlier (Mahajan et al., 2014).

2.1 Participants and stimuli

Six healthy, right-handed subjects (male/female: 3/3, age: 40±10 years) with no consumption of any medicine or drug prior to the test and without any reported neurological disorder who gave written consent prior to conducting the experiment, voluntarily participated in the experiment. All the participants equipped with Emotiv EEG headset were seated in a quiet and electromagnetic interference-free laboratory environment. The EEG signals from each subject were acquired by externally evoking them with diverse emotions of interest. Different emotional stimuli modalities used in the literature are audio, visual, a combination of both and self-recalling of a related incident (Mahajan et al., 2014). Auditory/music or audiovisual stimuli have been extensively used as an efficient emotion elicitor to detect emotions from resulting physiological activity (EEG) as both outperform the visual stimuli (Bos, 2006; Koelsch, 2011; Lin et al., 2010; Murugappan et al., 2009b; Scherer and Zentner, 2001; Zhou et al., 2014). Therefore, in this study, emotions were triggered using external music stimuli as well as self-recalling of a common depressive incident.

Figure 1 Block diagram of the proposed computer-aided and portable set-up for depression recognition using EEG-based affective brain mapping in real time (see online version for colours)

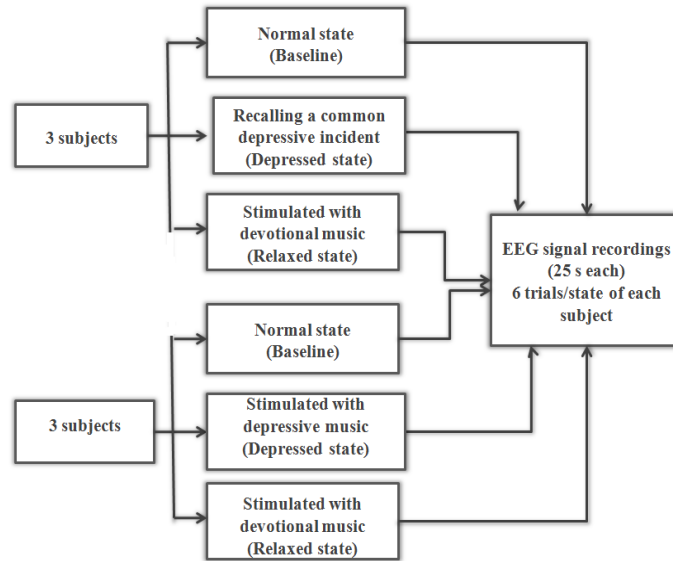


2.2 Experiment design

Emotion-related human EEG data set was constructed by following the experimental protocol depicted in Figure 2. The EEG signals for each subject were recorded under three states, namely normal (baseline), depressed (stimulated with depressed music/recalling a depressed incident) and relaxed (stimulated with devotional music). Each recording lasted for approximately 25 s with half a minute intrastate (inter-trials) and 1 minute interstate rest period in between. Two markers ‘start’ and ‘stop’ were set and sent manually at 5 and 25 s, respectively, so as to enable the extraction of distinct epochs from the recorded data set. The six subjects were divided into two groups, with each having three subjects. Initially, a baseline EEG was recorded corresponding to the normal state of each subject. After that, three subjects were made to listen to the selected depressive music, while the other three were asked to recall a common depressive incident related to their life to evoke depressive emotions. The corresponding human neural responses of each subject were recorded under depressed state category. Further,

the third set of EEG recordings belonged to relaxed state while subjects were stimulated using devotional music. The whole data set consists of more than 100 EEG records as each subject performed six experimental runs/trials per emotional state with an average duration of 25 s per record. At the end of the experiment, each participant was asked to rate the evoked emotion on a self-assessment criterion.

Figure 2 Schematic illustration of the experimental protocol followed to acquire emotion-specific EEG data set



2.3 EEG signal acquisition and recording

The real-time multichannel EEG recordings were acquired from subject's scalp using a high-resolution, cost-effective, portable and high-fidelity Emotiv EEG neuro-headset (Emotiv, 2014). It is capable of acquiring human brain activity via EEG using its 14 scalp electrodes (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4, with two reference electrodes CMS and DRL) placed over the frontal, temporal, parietal and occipital regions of the cerebral cortex (Mahajan et al., 2014). The acquired EEG data were filtered using a 0.16 Hz first-order high pass filter to remove the floating DC offset and background interferences, digitised with a 14-bit ADC, and were sampled at sampling frequency of 128 Hz. This 14-bit output was transmitted to a receiver laptop through a Bluetooth dongle and saved as a .edf (European data format) file. The data pack suite in Emotiv EEG test bench was analysed to ensure that there were no wireless dropouts during EEG data transmission.

2.4 Signal analysis and feature extraction

The multi-domain analysis of acquired EEG data set was done in *Affectiv suite* of Emotiv control panel, standalone *EEGLAB v 13.2.2b* application software toolbox in MATLAB workspace and *EDF Browser* application software platforms. Initially, real-time emotion

elicited variations in EEG were analysed using *Affectiv suite* of Emotiv control panel. It returns output emotional scores in terms of intensity level and consists of two graphs which can be customised to display different combinations of detections such as engagement, boredom, frustration, excitement and meditation in real time during different timescales.

Further, a multi-domain feature set constituting time domain (ERP), frequency domain (PSD, ASD) and channel coherence features of EEG was extracted and quantified to map the attained neural responses into consequent emotional states (normal, depressed and relaxed). Most of the shape-related information of a signal is indicated by its Fourier phase. Linear and second-order statistical measures fail to preserve the Fourier phase relationships and ignore certain random but important variations in non-linear, non-stationary and non-Gaussian EEG signals. On the other side, higher order statistics of order greater than two being a complex valued function possesses a property to preserve both magnitude and phase information of EEG signals (Chua et al., 2010). Therefore, by pre-processing EEG signals using fourth-order statistics-based Independent Component Analysis (ICA) techniques, a robust feature extraction methodology is presented here.

2.4.1 EEG pre-processing and data reduction

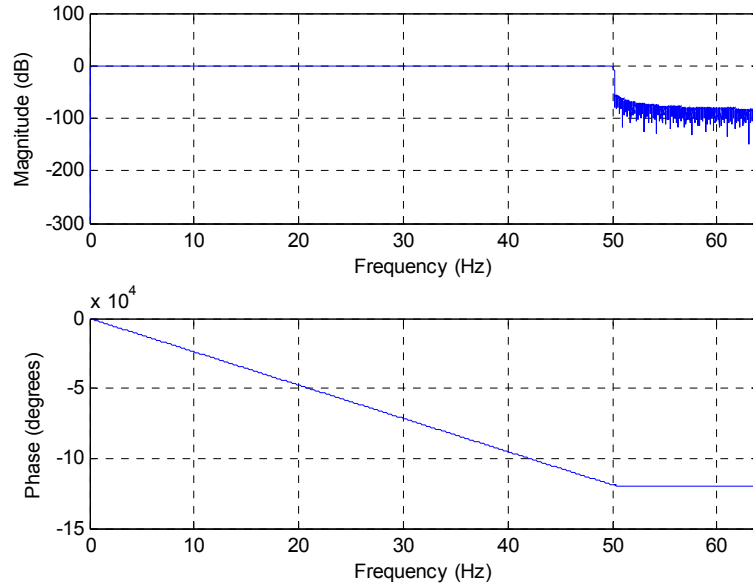
The emotion-specific recorded EEG data sets were imported to the *EEGLAB* to locate all 14 channels on the subject's scalp. Each record was band pass filtered using a 1691-point zero phase Finite Impulse Response (FIR) filter with transition bandwidth of 0.25 Hz and pass band edge as 0.25–50 Hz. The applied FIR Band Pass Filter (BPF) characteristics are plotted in Figure 3. This bandwidth allows characterisation of sub-band frequency variations to extract the different EEG band powers (delta, δ : 0.5–4 Hz; theta, θ : 4–8 Hz; alpha, α : 8–13 Hz and beta, β : 13–30 Hz). The phase delays introduced by the FIR BPF filter were nullified by applying filtering in reverse using MATLAB function *filtfilt()*. A fast and stable non-linear ICA decomposition algorithm '*JADE*' (Delorme and Makeig, 2004) was implemented in the present study to automatically reject eye blink and movement-related temporal/spatial artefacts and spurious epochs from imported neural signals. It utilises fourth-order statistics which is a measure of kurtosis (peakedness) of a signal and is thus more efficient in characterising unusual peaked distributions in attained EEG. The kurtosis is defined as (Delorme et al., 2007)

$$K = m_4 - 3m_2^2$$

and

$$m_n = E \left\{ (x - m_1)^n \right\} \quad (1)$$

where m_n represents fourth-order moment about the mean and E an average function. The strong positive and negative kurtosis values represent highly peaked artefacts, while near zero values are indicative of high Gaussianity (Delorme et al., 2007). The input EEG data sets were decomposed into maximally temporally and statistically independent components by measuring their non-Gaussianity and Fourier phase relations that get suppressed in Principal Component Analysis (PCA) decomposition based on second-order statistical measures (Joyce et al., 2004). Artefact-free clean EEG data were obtained by rejecting bad components possessing relatively high kurtosis values.

Figure 3 Finite impulse response band pass filter characteristics with pass band range 0.25–50 Hz (see online version for colours)

2.4.2 Channel ERPs and spectral analysis

The EEG potential and power distribution during distinct emotion elicitations were identified by extracting channel ERPs, channel spectral and channel activity plots, respectively. Event-related brain potentials are significant voltage variations resulting from brain activity triggered using external or internal stimuli. Distinct non-overlapped epochs of 500 ms prior to stimulus onset and 2000 ms after onset were extracted from each 25 s recording of EEG data set locked to emotions of interest. The extracted epochs were averaged in a digital domain with respect to repeated occurrences of distinct emotional events in a time-locked way. The high-resolution temporal patterns of neural responses (averaged ERP) with ERP scalp maps were computed at latencies corresponding to maximum ERP data variance to identify potential distribution across cerebral cortex. The associated ERP variations are plotted and quantified. The valence and arousal level (high and low) of evoked emotion were estimated from ERP image plots and distinct emotional labels were interpreted in context with Russell's (2010) 2D model of emotion. The ERP variations in the first half period of latencies are indicative of a subject's valence content while those in the later half reflect a subject's arousal level in response to triggered emotion (Picton, 1988; Kim et al., 2013).

The channel spectra and activity power spectrum of attained EEG data set with 2D topographic maps were plotted to locate emotion-activated scalp regions and determine associated EEG power distribution in four frequency sub-bands (δ , θ , α and β) during normal, depressed and relaxed states of mind. The sub-band with the maximum power concentration was identified as the dominant EEG frequency band. PSD ($\mu\text{V}^2/\text{Hz}$) and ASD ($\mu\text{V}/\text{Hz}$) of input EEG were computed (*EDF Browser*) at activated scalp regions to further quantify the emotion-induced spectral variations using FFT periodogram method.

A tapered Hanning windowing function with no phase shift was applied to attained EEG records before implementing FFT. This was done to eliminate the possibility of wrapping effects that are generally introduced as noise across the power spectrum. PSD is a measure of respective power strength at each frequency and is expressed as energy per frequency (Sanei and Chambers, 2007). Peak spectral power values ($\mu\text{V}^2/\text{Hz}$) were computed in the delta (PP_δ), theta (PP_θ), alpha (PP_α) and beta (PP_β) sub-bands. The Peak Frequency (PF) possessing the highest power in all sub-bands was identified to determine the dominant EEG frequency sub-band ($\delta, \theta, \alpha, \beta$) during distinct emotional states.

2.4.3 EEG cross-coherence

EEG cross-coherence was estimated to measure the degree of synchronisation between neighbouring neuronal activities by plotting their FFT spectrograms. EEG channel cross-coherence is defined as the correlation between two signals at different scalp electrodes at different frequencies. It is a function of individual power spectral densities of two selected channels and cross-PSD of both channels (Mathewson et al., 2012). The coherence between two EEG channels is given as

$$C_{ab} = \frac{\left(|P_{ab}(f)| \right)^2}{P_{aa}(f)P_{bb}(f)} \quad (2)$$

where P_{aa} and P_{bb} are the PSD of channels 'a' and 'b', respectively, at frequency f , while P_{ab} represents cross-PSD of channels 'a' and 'b' at frequency f . Lower coherence values reflect independent neural activity at each scalp location (little synchronisation), whereas higher values suggest more temporal coordination between the neuronal activity at two locations (Mathewson et al., 2012). Channel cross-coherence was retrieved between neural responses at spatially distinct pairs of electrodes placed over emotion-activated scalp regions to determine the EEG frequency sub-band possessing the maximum temporal, functional and phase connectivity during distinct emotional states.

2.4.4 Statistical data analyses

The discriminating ability and significance of extracted depression-related spectral feature set was tested using the *F-distribution* test in ANOVA. Group differences in peak EEG spectral power were examined during normal, depressive and relaxed states of mind in their respective identified dominant frequency sub-bands. Three groups (corresponding to three emotional states), each containing six entries (from six subjects) of respective peak spectral powers, were made and put to rigorous statistical analysis using the *F-distribution* test to analyse the statistical significance of the EEG inference data by estimating their *p-value*.

2.5 Algorithm development for depressive disorder diagnosis and management

As an outcome of the present study, an algorithm is designed in MATLAB to identify a 'depressed state' output by characterising EEG spectral power variations related to distinct emotion elicitations. The identified state may be used as an operative control output for automated depression management application. The recorded multichannel EEG data set is imported to MATLAB workspace using MATLAB function

edfread(filename). It returns all waveforms/data associated with imported file. The Emotiv electrode data from emotion-activated scalp regions are selected, baseline corrected and compressed using frequency transformation-based FFT technique. The compression is done to remove redundancy (to save signal storage space and transmission bandwidth), if any, while retaining the important diagnostic information in the reconstructed signal. The sub-band frequencies are set for δ (0.5–4 Hz), θ (4–8 Hz), α (8–13 Hz) and β (13–30 Hz) bands. The FIR BPF is configured at 128 Hz sampling frequency with slope roll-off rate at 6 dB per octave to compute PSD using FFT. The peak EEG sub-band power values are extracted and dominant EEG frequency sub-band is identified. The performance of applied compression technique is evaluated using compression ratio and Percent Root-Mean-Square Difference (PRD) (Velasco et al., 2007). The Compression Ratio (CR) is defined as the ratio of the number of bits representing input EEG to the number of bits representing compressed EEG. The distortion between the original and the corresponding reconstructed EEG signals is evaluated in terms of PRD error index and is calculated as

$$PRD = \sqrt{\frac{\sum_{n=1}^N (x[n] - \tilde{x}[n])^2}{\sum_{n=1}^N x^2[n]}} \times 100(\%) \quad (3)$$

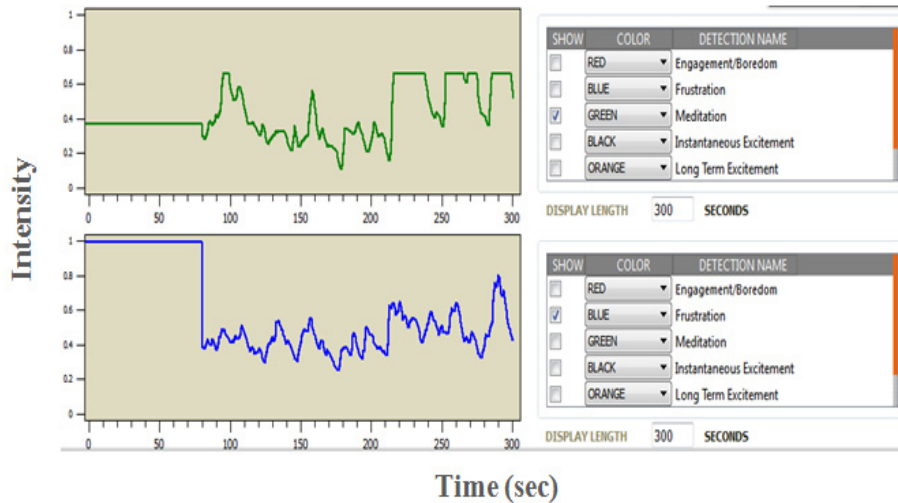
where $x[n]$ and $\tilde{x}[n]$ represent the original and the reconstructed signals, respectively, and N the number of samples. The higher the value of CR, the higher the degree of compression, and low PRD indicates efficient reconstruction of the EEG signal.

3 Results

This section presents the results of the experimentation. The proposed approach for depressive disorder diagnosis and management was developed and implemented in MATLAB 7.12 (R2013a), on an Intel core i5 processor with 3.20 GHz speed, 4 GB RAM and Microsoft Windows 7 Professional operating system. In this experiment, emotions of six human subjects were elicited using external music and the resulting neural responses via EEG were analysed. The ERP, channel spectral and channel coherence results of one subject are presented and discussed here, as a high incidence of similar results is found from other subjects as well. However, detailed comparative and statistical analysis of results of all the subjects is performed.

Primary online analysis of emotion-related variations in real-time EEG was done in *Affectiv suite* of Emotiv control panel as shown in Figure 4. The top graph was configured to plot 300 s of data for meditation detection (while stimulating the subject with external devotional music) and the bottom chart was customised to display 300 s of data for frustration detection (while stimulating the subject with external depressed music/recalling a depressed incident). Initially, the intensity level of frustration was found to be very high when the subject was stimulated with depressive music. As soon as the devotional music stimulus was triggered, a rise in intensity level of meditation was found as the intensity level of frustration decreased considerably (top chart). The results obtained are twofold: first, depression may ultimately lead to frustration and, secondly, it provides the basis that devotional music/meditation may be used as a subsequent therapeutic tool for depression management.

Figure 4 Online analysis of frustration vs. meditation results of Subject 1 captured in *affective suite* of emotive EEG control panel. Intensity level of frustration was found to be very high initially during depressive music stimulation (bottom chart). A rise in intensity level of meditation was observed during devotional music stimulation (top chart) (see online version for colours)



3.1 Channel ERPs and spectral analysis

Detailed offline analysis of acquired emotion-specific multichannel EEG data set was performed in *EEGLAB*. The emotion-related clean EEG epochs were extracted by rejecting highly peaked artefacts using fourth-order statistics (kurtosis) based ICA decomposition. The average ERPs were extracted during normal (baseline), depressed and relaxed states, and are shown in Figures 5(a), 5(b) and 5(c), respectively. Each trace in the resulting ERP plot indicates the average of the respective ERPs at a single channel. The 2D ERP scalp map's above traces show topographic distribution of average potential across the regions of cerebral cortex at maximum ERP data variance. The ERP data variance is found maximum at latency 945 ms during normal (Figure 5a), at 1570 ms during depressed (Figure 5b) and at 1695 ms during relaxed (Figure 5c) states of mind. The ERP scalp map in Figure 5(b) shows that frontal scalp regions possess maximum potential concentration (brighter red colour) during depressed state. It reflects that neural activity correlated to the emotion of depression can be captured prominently at the frontal channels, i.e. AF3 and AF4 of the Emotiv unit. Thus, EEG data epoch traces at AF3 and AF4 channel were extracted during normal, depressed and relaxed states. The maximum and minimum ERP, range, mean and standard deviation of ERP variations were identified and quantified in MATLAB, as depicted in Table 1. The amplitude and range of frontal ERPs are found to be more during depressed state in all subjects. Also, ERP variations were found to be highly correlated at channels AF3 and AF4 (Table 1) and thus may contain redundant information. This led to the selection of EEG records captured at AF3 channel (or AF4) for further analysis, thus minimising the total number of analyses. Figures 5(d)–5(f) show the EEG signal epoch trace captured at frontal channel AF3 during normal, depressed and relaxed states of Subject 1.

Figure 5 Average ERP with 2D scalp map of Subject 1 during (a) normal, (b) depressed and (c) relaxed states. ERP scalp map in (b) shows that frontal scalp regions (AF3 and AF4 channels) possess maximum potential concentration (brighter red colour) during depression elicitation. EEG signal epoch trace of Subject 1 at frontal channel AF3 during (d) normal, (e) depressed and (f) relaxed states showing maximum ERP amplitude and range during depressed state

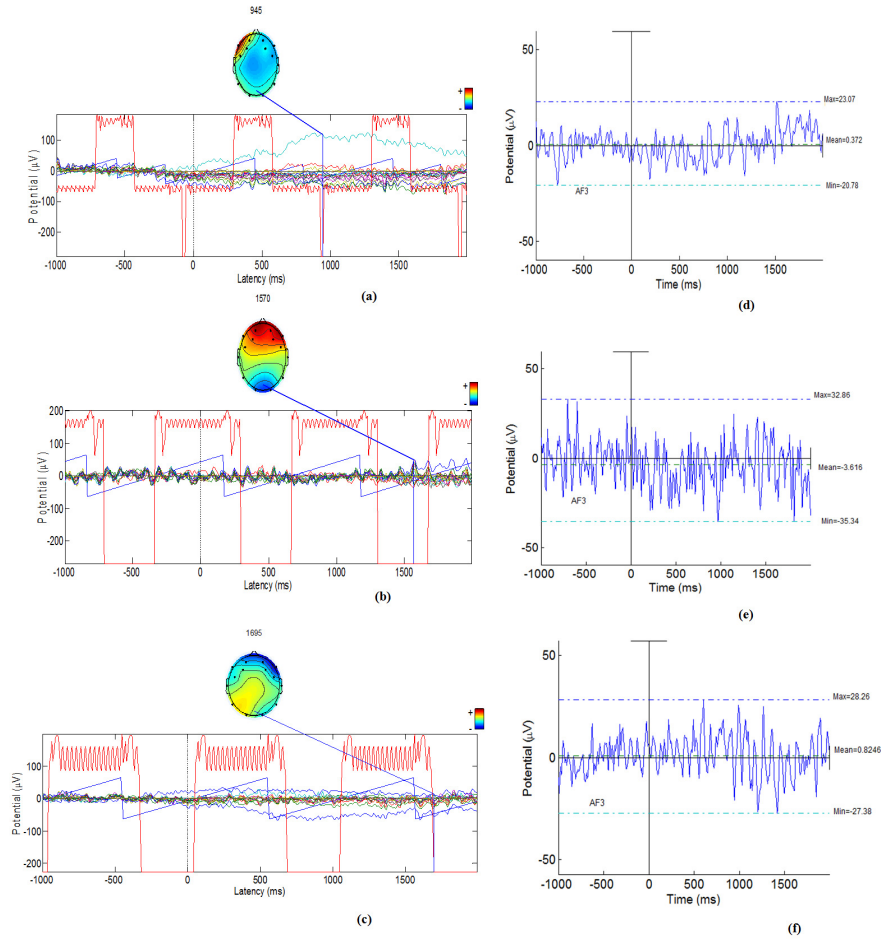


Table 1 ERP parameters at channels AF3 and AF4 during distinct emotional states of Subject 1

Sr. no.	ERP parameters	Normal state		Depressed state		Relaxed state	
		AF3	AF4	AF3	AF4	AF3	AF4
1	Maximum ERP (μV)	23.07	24.01	32.86	33.23	28.26	28.75
2	Minimum ERP (μV)	-20.78	-20.10	-35.34	-36.17	-27.38	-26.97
3	Mean of variations (μV)	0.3572	0.4144	-3.616	-2.981	0.8246	0.7813
4	Standard deviation (μV)	7.435	7.618	12.08	12.91	9.386	8.734
5	Range (μV)	43.85	44.11	68.21	69.40	55.64	55.72

The spectral variations in acquired multichannel EEG during normal, depressed and relaxed states were captured along with their 2D topographic activation maps in Figures 6(a)–(c). Here, each different coloured trace represents the spectrum of neural activity captured at different channels. The 2D scalp maps above show EEG power distribution in four frequency sub-bands (δ , θ , α and β). The leftmost scalp map in Figure 6(a) indicates that frontal scalp regions (identified as the maximum emotion-activated regions) are found to possess maximum delta power (at 2 Hz) concentration (red colour) during normal state of mind. However, these show maximum alpha power concentration (at 10 Hz, third scalp map, Figure 6b) during depressed state and delta power concentration (at 2 Hz, leftmost scalp map, Figure 6c) during relaxed state.

Further evidence to these results came from AF3 channel activity plots consisting of ERP image plot along with activity power spectrum in Figures 6(d)–(f). The valence (ERP variations in the first half of period of latencies) and arousal (ERP variations in the later half of period of latencies) content in attained neural activity was encoded from different colour-coded values obtained in a rectangular ERP image plot. Here, a red coloured bar represents the moment of subject's maximum response to stimulus, whereas a blue bar indicates the moment of minimum response. The high valence content (more red coloured bars in the first half of period of latencies, -1000 to 250 ms) and gradually increasing arousal content (red bars in the later half period, 250 – 1500 ms) are found during normal state (Figure 6d). This, in turn, reflects a satisfactory/pleasant mind in accordance with Russell's 2D model of emotion. Further, low valence content can be inferred from few red bars in the first half, indicating towards unpleasant/stressed mind of subject while being stimulated with depressed music (Figure 6e). A gradually increased valence content (towards the end of the first half period) and a very high arousal level (dense red bars in the later half period) represents a happy/pleasant mind with gradual disappearance of unpleasantness while being stimulated with devotional music (Figure 6f). The trace below the ERP image shows the ERP average of the epoched data set and the red dot in the scalp plot locates the position of the AF3 channel (Channel 3 of Emotiv unit) selected to observe emotion-elicited neural activity response. The activity power spectrum below shows spectral variations in terms of log transformed ($\mu\text{V}^2/\text{Hz}$) power. A peak log transformed delta band power of approximately $18 \mu\text{V}^2/\text{Hz}$ (highlighted with green box in Figure 6d) is found during normal, peak alpha band power of $20 \mu\text{V}^2/\text{Hz}$ (Figure 6e) during depressed state of mind and peak delta band power of $19 \mu\text{V}^2/\text{Hz}$ (Figure 6f) is found during relaxed state of mind. It can also be noted that normal (baseline) and relaxed states (elicited using devotional music) show high correlation as delta band power is found to be high in both states at frontal scalp regions, strengthening our primary hypothesis that devotional music can be developed as a subsequent therapeutic tool for depressive disorder management.

3.2 EEG cross-coherence

The FFT-based spectrograms in Figures 7(a)–(c) show cross-coherence between neural activations captured at frontal channels (AF3 and AF4) during three emotional states. The upper panel depicts the event-related functional and phase synchronisation, whereas the lower panel indicates phase difference between them. Clusters of high delta (0.5 – 4 Hz) coherence (highlighted area with red circle in Figures 7a and 7c) are observed in resulting spectrograms (red spots) during normal and relaxed emotional states. However, greater alpha (8 – 13 Hz) coherence is found during depressed state (Figure 7b).

Instances of high coherence (red spots in upper spectrogram) are found to possess minimum phase difference (characterised with green colour in lower spectrogram) between frontal scalp neural activities. A substantial synchronisation between neuronal activities at the frontal brain regions (delta coherence during normal and relaxed; alpha coherence during depressed state) are found during emotion analysis.

Figure 6 Channel spectra and corresponding scalp maps of epoched data set of Subject 1 during (a) normal, (b) depressed and (c) relaxed states showing EEG power distribution in four frequency sub-bands (δ , θ , α , β). Channel activity results containing ERP-image plot and activity power spectrum captured at left frontal channel AF3 of Subject 1 during (d) normal, (e) depressed and (f) relaxed states reflecting maximum alpha power (8–13 Hz) concentration during depressed state and delta power (0.5–4 Hz) concentration during normal and relaxed states (highlighted with green box)

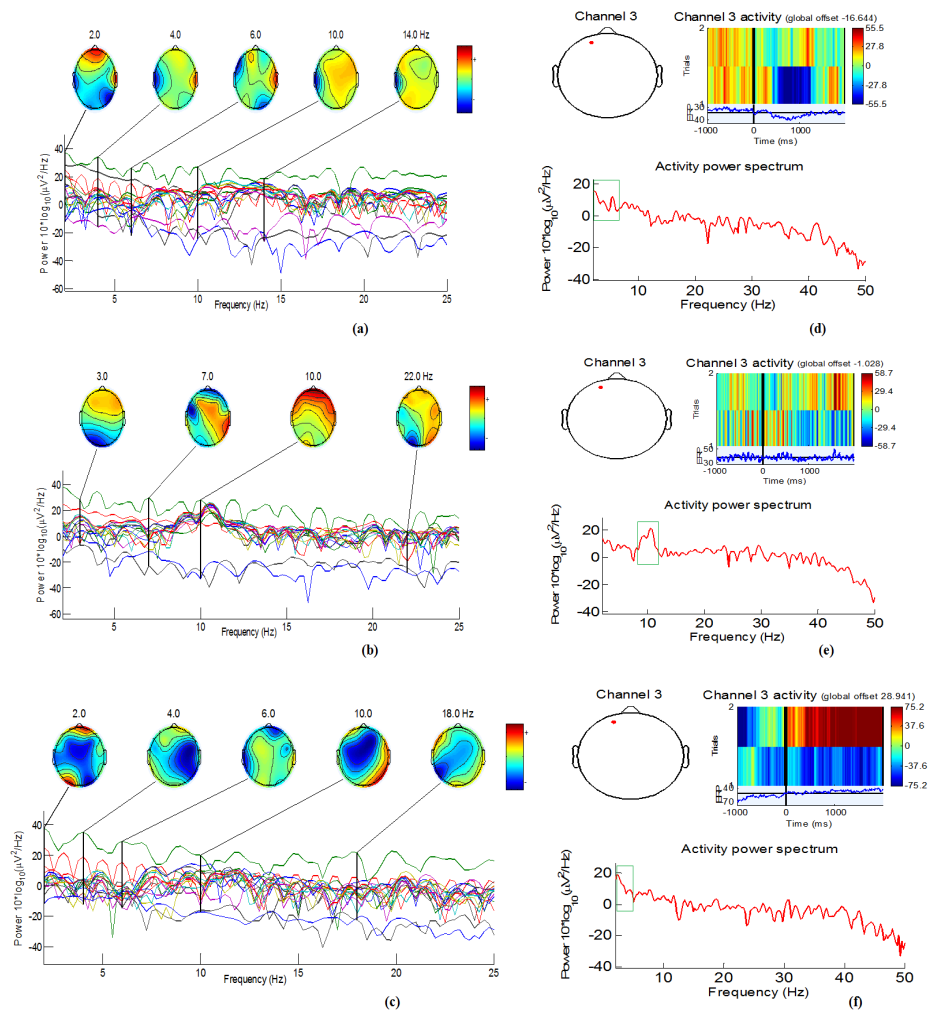
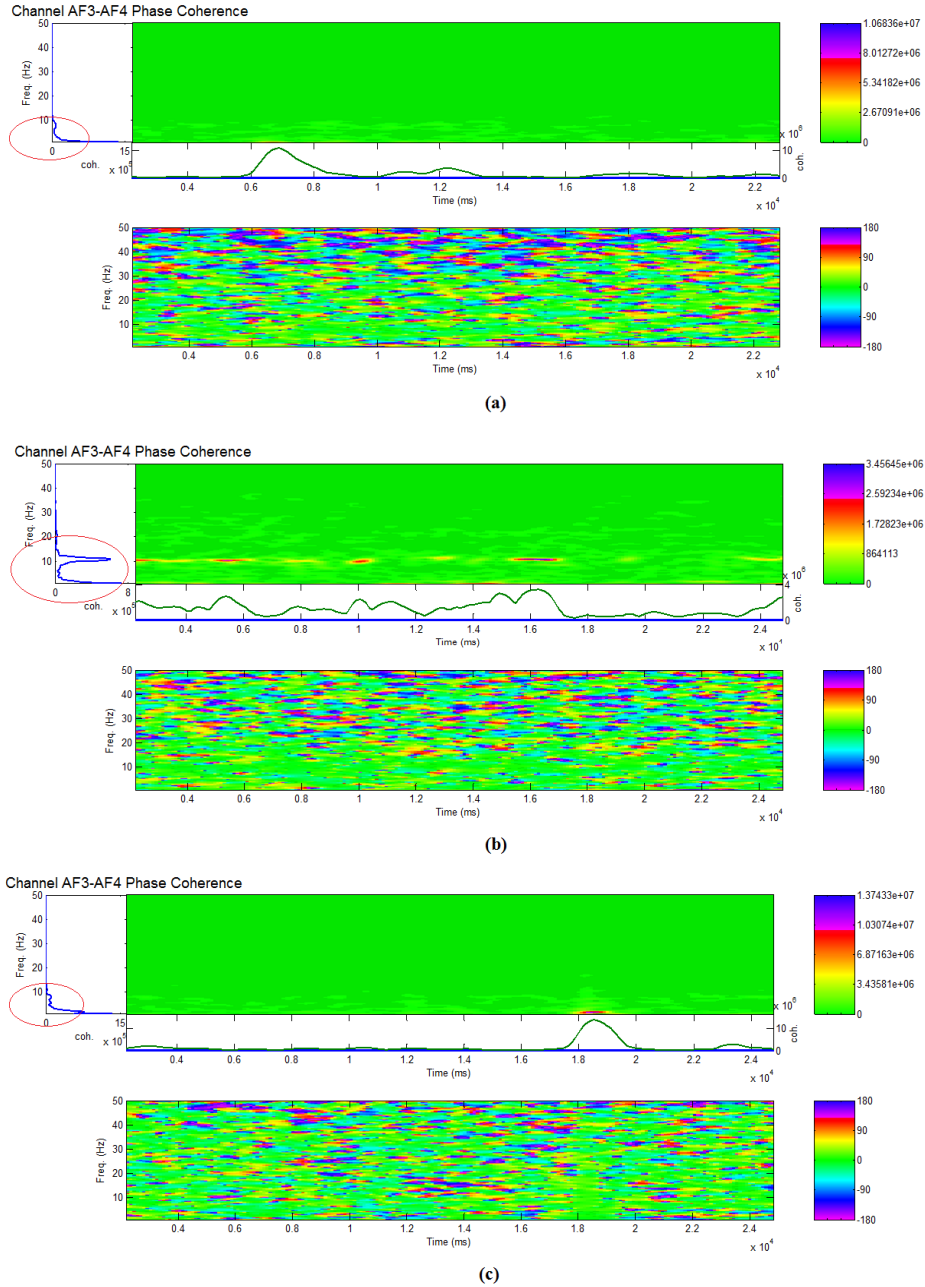


Figure 7 Channel cross-coherence between neural activity captured at frontal channels AF3 and AF4 during (a) normal state, (b) depressed state and (c) relaxed state of Subject 1, indicating clusters of high alpha coherence (8–13 Hz) during depressed state and high delta coherence (0.5–4 Hz) during normal and relaxed states (highlighted with red circle in upper left panel)



3.3 *Quantified EEG sub-band power*

Peak delta power (PP_δ), peak theta power (PP_θ), peak alpha power (PP_α) and peak beta power (PP_β) were determined at the frontal AF3 electrode by computing PSD (Figures 8a–8c) and ASD (Figures 8d–8f) during three emotional states. The detailed comparative analysis of peak power scores of all subjects is performed in Figures 9(a) (peak delta power), 9(b) (peak theta power), 9(c) (peak alpha power) and 9(d) (peak beta power). The peak power frequencies (PF) and respective peak power value results captured from all subjects are tabulated in Table 2. No significant increasing/decreasing diagnostic trend/consistent pattern is observed in theta and gamma band powers (Figures 9b and 9d) during the selected three emotional states, while alpha and delta band powers show large variations (Figures 9a and 9c). The normal and relaxed states of mind are found to be correlated with elevated delta power values (Figure 9a), whereas peak alpha power values are found to be more during depressed state (Figure 9c). Depressive state was triggered in the first three subjects by asking them to recall a common depressive incident of their life, whereas depressive music was used to stimulate the other three. Though results of the first three subjects show high elevation of alpha band power as compared to the other three, a similar increasing trend in alpha band power can be observed as a whole (Figure 9c) in all six participants during depressed state of mind while delta band power is simultaneously decreasing (Figure 9a).

3.4 *Statistical data analyses*

One-way ANOVA was performed on maximum delta and alpha band power values individually captured from six subjects during six trials per emotional state. The F -distribution score-based statistical method was adapted to evaluate significant differences between emotion-related neural activation, which is defined as the between-group variance divided by the within-group variance. The larger the F -distribution score, the greater the discrimination power (Lin et al., 2010). At first, three groups containing six entries of peak delta power values corresponding to each subject's six trials during normal, depressed and relaxed states were defined. This was followed by defining similar three groups containing peak alpha power values. Group differences in peak delta and alpha power values were determined during normal, depressed and relaxed states of mind. Table 3 provides a list of significant statistical parameters obtained using one-way ANOVA for specified EEG features to examine the variations among three emotional states. Significant differences were observed in EEG delta spectral power ($F(3,18) = 11.3820$, $p = 0.00098310$ (<0.001)) and alpha spectral power ($F(3,18) = 7.0143$, $p = 0.00707$ (<0.001)) among three emotional conditions, thus indicating statistically significant discriminating ability of delta and alpha spectral power in depression detection.

Figure 8 Power spectrum of EEG signal acquired at left frontal channel AF3 of Subject 1 during (a) normal state, (b) depressed state and (c) relaxed state; and respective amplitude spectrum during (d) normal state, (e) depressed state and (f) relaxed state. It shows dominant alpha wave component during depressed and dominant delta wave component during normal and relaxed state with their respective peak sub-band power and amplitude magnitudes

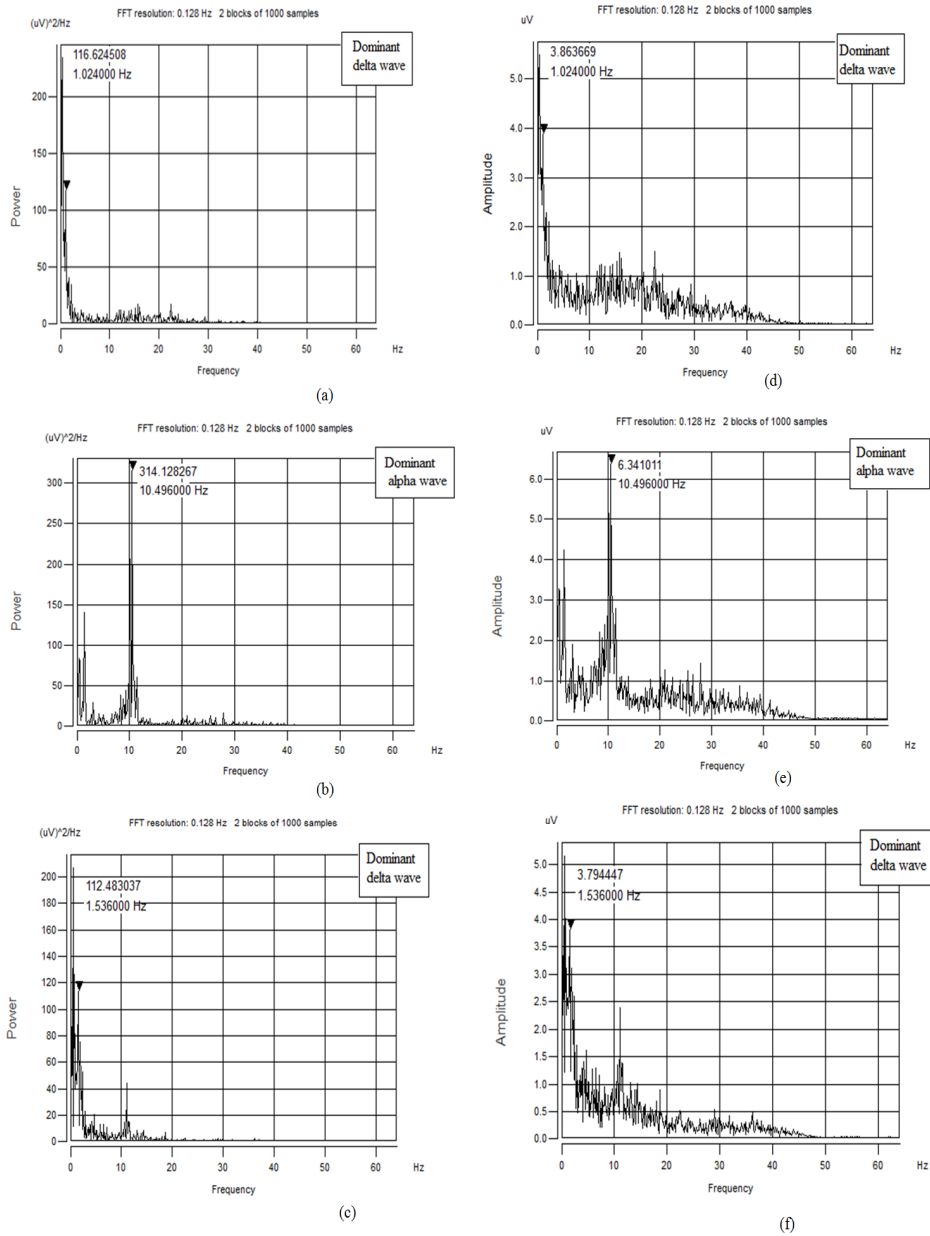


Figure 9 Bar charts showing the comparison of (a) peak delta power, (b) peak theta power, (c) peak alpha power and (d) peak gamma power; captured at the left frontal channel AF3 of six subjects during their normal, depressed and relaxed states of mind (see online version for colours)

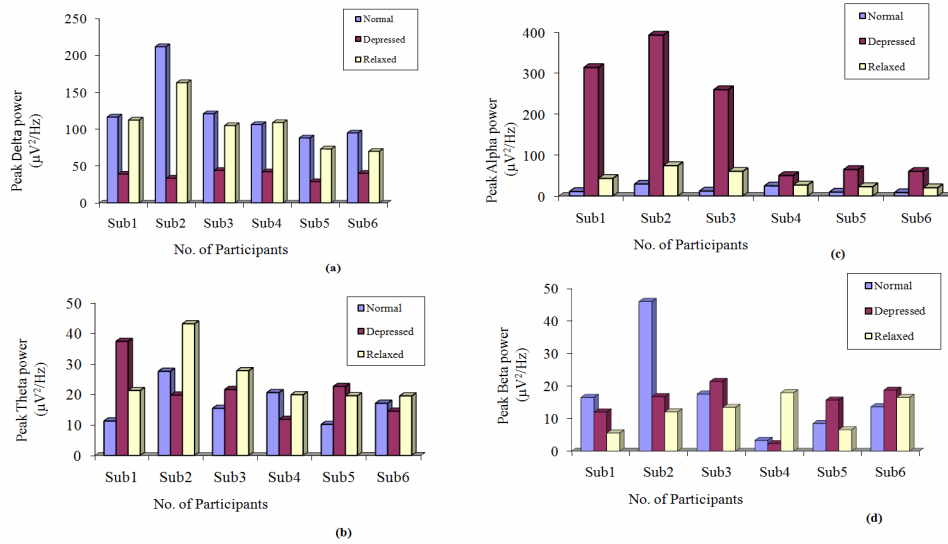


Table 2 Peak power and respective Peak Frequencies (PF) captured at frontal channel AF3

Subjects	Normal state		Depressed state		Relaxed state	
	Peak power ($\mu V^2/Hz$)	PF (Hz)	Peak power ($\mu V^2/Hz$)	PF (Hz)	Peak power ($\mu V^2/Hz$)	PF (Hz)
Sub 1	116.624	1.024	314.128	10.496	112.483	1.536
Sub 2	212.105	1.280	393.361	10.752	163.246	1.280
Sub 3	121.413	1.072	260.354	9.472	105.231	1.048
Sub 4	107.536	1.640	49.00	9.0880	109.308	1.640
Sub 5	88.311	1.792	64.243	10.752	73.172	1.024
Sub 6	95.815	1.048	60.117	10.325	70.519	1.920
Dominant EEG band ($\delta, \theta, \alpha, \beta$)	δ (0.5–4 Hz)		α (8–13 Hz)		δ (0.5–4 Hz)	

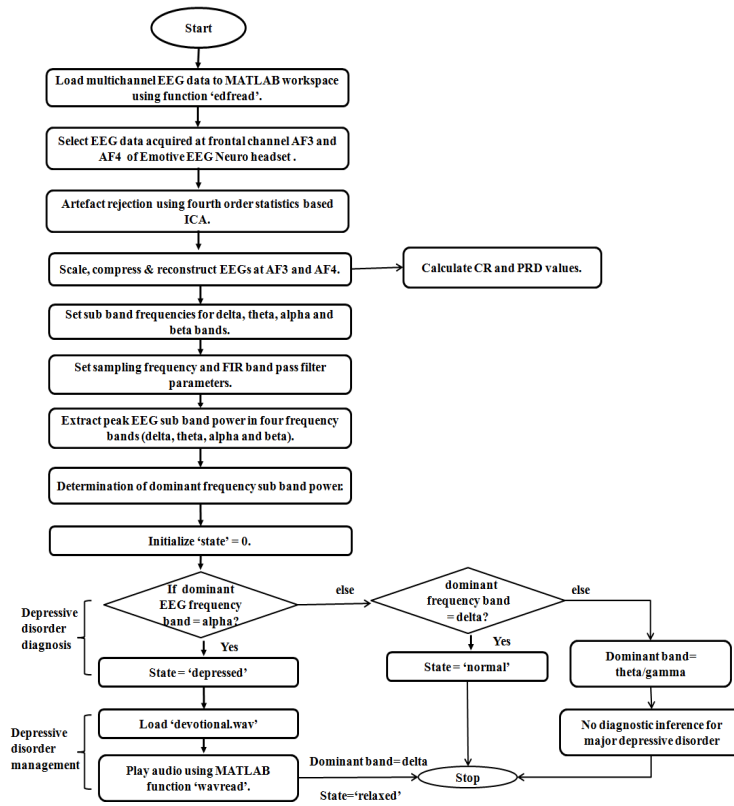
Table 3 One-way ANOVA (*F*-distribution test) parameters

Sr. no.	Statistical parameters	EEG features	
		Delta spectral power	Alpha spectral power
1	Number of groups/states	03	03
2	Number of entries per group	06	06
3	Between group variance, MS_{bet}	12190.5001	54521.5557
4	Within group variance, MS_{within}	1071.0333	7772.8889
5	<i>F</i> -value	11.3820	7.0143
6	<i>p</i> -value	0.00098310 ($p < 0.001$)	0.00707113 ($p < 0.01$)
7	Statistically significant/non-significant	Highly significant	Significant

3.5 Algorithm development for depressive disorder diagnosis and management

The twofold labelling of acquired EEG data into three emotional states has been done by analysing participants' self-assessments and the corresponding Emotiv control panel's *Affectiv suite* results in real time. A significant correlation is found between a subject's subjective reporting of the emotional experiences during the session and *Affectiv suite* results. No significant difference appeared in results by either sex or age. This characterisation of emotion-related EEG using multi-domain feature and topographic analysis is further utilised to design an algorithm in MATLAB (Figure 10) to identify a 'depressed state' output during dominating alpha band power at frontal channels. This may be used as an automated operative control signal to play an audio file 'devotional.wav' (using MATLAB function *wavread(filename)*) in depression management application as shown in Figure 10. The acquired frontal scalp EEG activity is found to be highly correlated at AF3 and AF4 channels of Emotiv unit, thus showing redundant information. The FFT-based compression is applied to remove redundancy. High compression ratio while retaining low percentage of root-mean-square errors ($CR = 21.2384$, $PRD = 0.1451\%$) are achieved, thereby preserving significant clinical information even after compression. This reflects that EEG sub-band power-based affective brain mapping can be used to develop a diagnostic tool for automated depressive disorder diagnosis and management application.

Figure 10 Algorithm to use EEG sub-band spectral power as a trigger for depressive disorder diagnosis and management application



4 Discussion

The present research investigated whether normal state EEG potential distribution (ERP variations), power distribution (spectral power variations) and event-related coherence in four frequency bands (δ , θ , α and β) are distinct from those in major depressive disorders. Frontal elevated alpha power and alpha coherence is observed during a depressed state of mind, whereas the normal and relaxed states are found to be correlated with increased delta power and delta coherence at frontal scalp regions. Increased alpha activity at frontal regions may indicate brain inactivity (Mathewson et al., 2012; Niemic, 2002), thus in turn a less attentive/receptive and more inhibited brain during depressed state. On the other hand, desynchronised alpha activity is reported in the literature to be associated with increased neuronal excitability (Mathewson et al., 2012). Reduced frontal alpha power and alpha coherence may reflect enhanced brain activity, thus more attentive and receptive brain during normal and relaxed state. Therefore, it can be summarised from reported relations that characterisation of frontal alpha and delta band power as well as coherence may be developed as a computer-assisted diagnostic tool for depressive disorder via EEG, whereas devotional music can be established as a therapeutic tool to assist patients with major depressive disorder. In contrast to previous reports showing correlation of depression with anterior/posterior cortex of the brain (Fingelkurts et al., 2006), increased frontal theta activity and increased frontal temporal beta activity (Marosi et al., 2001), the present study found it to be correlated with increased frontal alpha activity. However, these findings appear to accord well with a previous work showing pre-frontal region activity during depression (Cook and Leuchter, 2001).

Further, the proposed EEG-based affective brain mapping was implemented on EEGs acquired for a duration of 25 s each since the reliability of EEG measures and their clinical relevance is reported to be high only for epochs with marginal length not more than 40 s (Gudmundsson et al., 2007). Emotional states of interest were evoked using external music stimuli as it has been proved to be an efficient emotion elicitor in the literature (Bos, 2006; Koelsch, 2011; Lin et al., 2010; Murugappan et al., 2009b; Scherer and Zentner, 2001; Zhou et al., 2014). Fourth-order statistics-based ICA was successfully implemented to capture and reject eye blink and movement-related artefacts from acquired EEG. Being a non-linear technique, it has been proved to be a more efficient method to characterise non-linear temporal and morphological variations in EEG by measuring their Fourier phase relations and deviations from Gaussianity as compared to PCA (Delorme and Makeig, 2004; Delorme et al., 2007; Joyce et al., 2004). The ERP image plots and *Affective suite* results indicate that depression is found to be associated with decreased valence content and thus unpleasant/frustrated behaviour, whereas at the moment of devotional music stimulus onset, a decrease in frustration can be observed with increasing valence content. Therefore, the use of devotional music may also provide the possibility of getting rid of side effects associated with certain antidepressant drugs and therapies.

Development of automated diagnostic tools based on artificial intelligence techniques is of utmost importance to aid clinicians as non-availability of any standard laboratory test for the same may cause misdiagnosis. However, the current methodology in distinguishing depressed subjects from healthy normal subjects is proposed using more than 100 EEG data sets from only six subjects. The validity on extended EEG data obtained from large sample of subjects shall be carried out as our future work to develop a more robust depression diagnostic tool based on efficient machine learning techniques as an outcome.

5 Conclusion

An attempt has been made to develop an efficient EEG-based affective brain mapping tool for early and accurate diagnosis of depression using external music stimuli in real time. Channel ERPs, cross-coherence and spectral analysis techniques are explored along with their detailed topographic analysis to map the attained EEG data into consequent emotional states. It is observed that frequency sub-bands possessing the psychiatric coherence in depressive disorder diagnosis are delta (0.5–4 Hz) and alpha (8–13 Hz). The frontal scalp regions appear to be incorporated with increased delta power and delta coherence during normal (baseline) and relaxed (stimulated with devotional music) states of mind, whereas increased alpha power and alpha coherence can be seen during depressed state of mind. The results reported here with minimal p -values are suggestive of the consistency and statistically significant discriminating ability of EEG spectral power (delta and alpha) in conjunction with fourth-order statistics-based ICA towards depressive disorder diagnosis and management. An algorithm is designed as an outcome of this research, to identify and translate a ‘depressed state’ output into automated operative control signals to trigger devotional music-based depression management application. The inferences drawn from the results demonstrate the potential of the proposed algorithm to be developed as a promising computer-aided diagnostic and management tool for depressive disorder. This may further prove helpful in managing a variety of depression-related neurological syndromes such as stress, frustration, anxiety, sleeping disorders, pessimism, immune system disorders, risk of death, etc., at early stages with proper treatment planning. Efforts are underway to validate the current methodology on extended data obtained from large sample of subjects while studying the inter-variability between subjects.

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