JOURNAL OF INFORMATION SCIENCE AND ENGINEERING 35, 577-595 (2019)
DOI: 10.6688/JISE.201905_35(3).0006

Regression Analysis of Coherence between Concurrent EEG-EEG and EEG – CPPG Signals from Prefrontal Cortex During Music Evoked Emotions

REVATI SHRIRAM[1,5], V. VIJAYA BASKAR[2], BETTY MARTIN[3],
M. SUNDHARARAJAN[4] AND NIVEDITA DAIMIWAL[5]
[1,2]*Electrical and Electronics Department*
Sathyabama Institute of Science and Technology
Chennai, 600119 India
[3]*Shanmuga Arts Science Technology Research Academy*
Thanjavur, 613401 India
[4]*Bharath Institute of Higher Education and Research*
Chennai, 600073 India
[5]*Cummins College of Engineering for Women*
Pune, 411052 India
E-mail: revatishriram@yahoo.com

This paper summarizes the results of experiment that focus on effect of music evoked emotions on mean squared coherence and phase coherence between two signals with same nature (electrical brain signal – EEG) and the two signals with different nature (EEG and hemodynamic brain signal CPPG). Regression analysis was carried out to find out the mathematical relation between mean squared coherence and phase coherence estimated between the two signals captured from prefrontal cortex and the physiological parameters. Number of synaptic connections between the two measurement sites/ signals and its strength is reflected in the coherence. It is a quantitative measure of association between the two simultaneously acquired signals as a function of frequency. Physiological parameters studied by the authors are SBP, DBP, HR, Blood Glucose and BMI. These are some of the potential biological markers closely related to emotional response. Data was collected from twenty multi-lingual subjects of both the genders with $Mean_{age}$ = 39.25 years and SD_{age} = 11.625 years. No strong correlation was found between the coherence (calculated between EEG-EEG and EEG-CPPG) and the physiological parameters studied during the various emotional states. It was observed that MS Coherence between the signals with similar nature is higher than it in between the signals with dissimilar nature. T-paired test was carried out to show that the means of these two coherences is different. Coherence between EEG-EEG was compared with coherence between EEG-CPPG and it was observed that they are very different ($p < 0.001$), were as when coherence between EEG-EEG (or EEG-CPPG) is compared with coherence between EEG-EEG (or EEG-CPPG) p-value was > 0.05. This technique can be applied to wider population in the field of clinical neuroscience with or without any known neurological disorder. More connectivity measures can also be included to study music evoked emotions or stroop task.

Keywords: cranial photoplethysmogram, electroencephalogram, emotions, mean square coherence, phase coherence, physiological parameters, regression analysis

1. INTRODUCTION

Common definition of emotion is, it is a biological action which plays important role in the determination of behaviour of a person. Emotion is made of three components:

Received January 3, 2018; revised June 22, 2018; accepted August 27, 2018.
Communicated by Wen-Liang Hwang.

expressive component, subjective component and physiological component. Listening to music is an easy and quick activity to express and induce various emotions. Music based emotions are explained as a process that is influenced by various components such as individual attributes (such as personality and preference of music), musical attributes (such as harmony, music genre, tempo) and contextual attributes (such as multimodal information and connection of music with everyday activities) [1-5]. Electroencephalogram (EEG) an electrical brain signal and Cranial Photoplethysmogram (CPPG) a hemodynamic brain signal are recorded from prefrontal cortex simultaneously with systolic and diastolic blood pressure, heart rate, are some of the potential biological markers related to emotional activity. In the recent studies with EEG and Functional Near Infrared Spectroscopic Signal (fNIRS, in our case this same signal is CPPG) it has been observed that prefrontal cortex is a key region in experiencing and regulating emotional responses [6-10]. It is expected that CPPG, EEG and autonomic variations (such as blood pressure, heart rate, respiratory rate, urination and digestion) are found to be highly coherent with each other. [2] Where EEG and CPPG are fast varying signals as compared to the variations observed in the various physiological parameters.

Changes in brain activity are closely coupled with changes in blood flow in those areas, this is useful in mapping brain functions in humans [11, 12]. With change in cognitive or behavioural demands, it increases the neuronal activity induced changes in regional blood flow and in turn change in blood volume [13]. Due to neurovascular coupling (it is the relationship between neuronal activity and the subsequent cerebral blood flow (CBF) change) there is a change in blood oxygen content. In clinical settings, brain images showing active and inactive area are created based on the hemodynamic response in that brain region. This can be a useful tool in diagnosing neural disease or in pre-surgical planning. Functional MRI (fMRI) and Position Emission Tomography (PET) scan are the most common techniques that use hemodynamic response to map brain function. Fig. 1 shows how human brain responds to any activity and how EEG and CPPG signal originates.

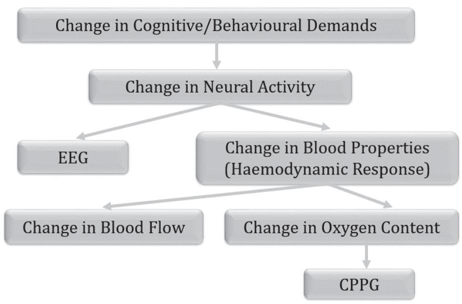

Fig. 1. Response of brain to any activity.

Functional linkage between the brain region can be given by coherence. Coherence is of two types, magnitude square coherence and phase coherence, it is a quantitative measure of association between the two simultaneously acquired signals as a function of frequency. It is one of the widely studied connectivity measure in EEG related studies. Number of synaptic connections between the two measurement sites/signals and its strength is reflected in the coherence. It was found that high coherence occurs during the epileptic seizures (one of the most common neurological disorder) and in subjects with mental retardation. Low coherence is also a sign of inappropriate brain functions due to neurological disorders [14-16]. Coherence is a complex mathematical relation between the two signals but it can be explained in simplest way as: measure of a degree to which the two simultaneously acquired signals are in a phase locked relationship over a time at a given frequency. If the phase angle between the two signals is constant at a given frequency then the coherence is ~1. If random phase relationship is followed by the two signals then the coherence is ~0. Coherence is independent of amplitude of a signal but it entirely depends on the ways signal fluctuates. Other connectivity measures that can be applied to the any simultaneously acquired data are as shown in Table 1. Power spectral density of the signal is estimated using welch method before calculating coherence.

Table 1. Various functional connectivity measures and description [1, 17-20].

Connectivity Measures	Description of Connectivity Measures
Coherence	Linear correlation between the two signals as a function of frequency.
Correlation	Pearson's correlation coefficient zero lag.
Cross-Correlation	Linear correlation between the two signals as a function of time.
Direct Transfer Function	It is like partial directed coherence; however direct transfer function uses a Hermitian Transpose instead of a Fourier Transform.
Granger Causality	It is a linear parametric method, measures if signal '*x*' provides predictive information about signal '*y*'.
Partial Directed Coherence (PDC)	It is a frequency domain measure of Granger Causality, based on modelling time series by multivariate autoregressive process (MAP).
Phase-Lag Index (PLI)	It is a measure of phase synchronization like Phase Locking Value, however it rejects phase distribution centred around zero.
Phase-Locking Value (PLV)	It is a measure of phase synchronization. It gives inter-trail variability of the phase difference between the two signals at a time '*t*'.
Phase Slope Index	It is the estimation of flow direction of information between two signals as a function of time.
Transfer Entropy	It is a non-parametric measure of amount of directed information flow from signal '*x*' to '*y*'.

Power Spectral Density (PSD)

PSD shows the strength of energy variations as a function of frequency. It is the Fourier transform of auto covariance function [21]. The unit of PSD is the energy/frequency (width). It is the powerful tool to identify the oscillatory (non-stationary) signals in the time series. It provides the important information about the frequency range in which the power variations are strong; this information can be used for further analysis. PSD is given by the any of the following equations [21-25].

$$\varnothing(w) = \sum_{k=-\infty}^{\infty} r(k)e^{-jwk} \tag{1}$$

$$\varnothing(w) = \lim_{N\to\infty} E\{\tfrac{1}{N}\left|\sum_{t=1}^{N} y(t)e^{-jwt}\right|^2\} \tag{2}$$

Cross Power Spectral Density (CPSD)

CPSD is the Fourier transform of cross-covariance function. When $X = Y$ then CPSD reduces to the PSD. For real signals $Y^*(w) = Y(-w)$; where '*' denotes the complex conjugate. CPSD is complex because the cross covariance is asymmetric. The PSD is real because the auto-covariance is symmetric. Then CPSD is given by:

$$CPSD_{XY}(w) = X(w)Y^*(w). \tag{3}$$

Coherence

Spatial analysis of EEG or CPPG means the joint observation of time series of data channels. Coherence is a linear correlation coefficient that gives the phase synchronization between the data channels. Coherence depends on two parameters: relative phase and relative amplitude at each frequency between the two concurrently acquired EEG signals or concurrently acquired EEG and CPPG signals.

(a) Magnitude Coherence Function

$$C_{xy}(w) = \frac{P_{xy}(w)}{\sqrt{(P_{xx}(w)P_{yy}(w))}} \tag{4}$$

Where P_{xx} & P_{yy} are power spectra of signals 'x' & 'y'. P_{xy} is the cross power spectra of signals 'x' & 'y'.

$$P_{xy}(w) = \hat{x}(w) * \overline{\hat{y}(w)} \tag{5}$$

$$P_{xx}(w) = \hat{x}(w) * \overline{\hat{x}(w)} = |\hat{x}(w)|^2 \tag{6}$$

$$P_{yy}(w) = \hat{y}(w) * \overline{\hat{y}(w)} = |\hat{y}(w)|^2 \tag{7}$$

Where $\overline{x}$ and $\overline{y}$ are the complex conjugates of 'x' and 'y' [21-27].

(b) Phase Coherence Function

Phase coherence is denoted by $\varnothing(w)$ and is given by:

$$\varnothing(w) = \tan^{-1}\left\{\frac{Im[P_{xy}]}{Re[P_{xy}]}\right\}. \tag{8}$$

The degree of synchronization between the EEG signals is characterized by magnitude and phase coherence. Another method is to find the wavelet coherence. It gives the information not only about the frequencies but the time at which they appeared.

Cross Covariance

It is the function which gives the covariance of one signal with the other at a given point. Covariance of two signals is the tendency to co-vary or move together. It is useful in identifying the lag of signal 'x' which will be useful in prediction of signal 'y'. It is the commonly used tool in the multiple time series analysis. Cross covariance is given by:

$$\sigma_{xy}(T) = \tfrac{1}{N-1}\sum_{t=1}^{N}(x_{t-T} - \mu_x)(y_t - \mu_y). \tag{9}$$

Where x_t and y_t are the two signals and x_t is delayed by T samples. μ_x and μ_y are the means of two signals with N samples in each. σ_{xy} is the cross-covariance function. Cross correlation is the normalized version of cross-covariance as follows:

$$r_{xy}(T) = \frac{\sigma_{xy}(T)}{\sqrt{\sigma_{xx}(0)\sigma_{yy}(0)}}. \tag{10}$$

Where $\sigma_{xx}(0) = \sigma_x^2$ and $\sigma_{yy}(0) = \sigma_y^2$ are the variances of each signal. Positive covariance signifies that larger value of signal 'x' are associated with the larger values of signal 'y'. In negative covariance larger values of 'x' are associated with smaller values of 'y' and vice a versa.

Cross Correlation

It is the oldest and simplest classical measure of interdependence between the signals. Linear cross-correlation is the most widely used and simplest measure of synchronization. Cross-correlation compares the two signals by shifting one of them relative to the other. It is the generalization of standard linear correlation analysis. In the time domain it is given by the function of time lag τ: $\tau = -(N-1), \ldots, 0, \ldots, (N-1)$ is derived from normalized signals X_n and Y_n of length 'N' with zero mean and unit variance as:

$$C_{xy}(\tau) = \begin{Bmatrix} \tfrac{1}{N-\tau}\sum_{n=1}^{N-\tau} x_n + ry_n & \tau \geq 0 \\ C_{xy}(-\tau) & \tau < 0 \end{Bmatrix}. \tag{11}$$

Square of correlation coefficient is similar to the coherence and to the coefficient of determination. Correlation is sometimes used as coherence and is given by:

$$\rho^2 = \frac{|\operatorname{cov}[x,y]|^2}{\operatorname{var}[x]\operatorname{var}[y]}. \tag{12}$$

2. SUBJECT AND METHODS

Fig. 2 shows the system block diagram. Concurrent acquisition of EEG and CPPG from prefrontal cortex is carried out by using PowerLab based EEG acquisition and CPPG is captured by using the sensor developed by the authors. Reflective type of CPPG sensor consists of IR LED of 860 nm wavelength and OPT 101 (silicon burr brown diode) as a detector. MATLAB 2010 based coherence estimation was carried out by the authors. Further regression analysis between the MS Coherence/Phase Coherence and the physiological parameters was carried out by using MINITAB 17 software. Fig. 3 shows the system setup for concurrent acquisition of EEG-EEG and EEG-CPPG signal during music evoked emotions. Table 2 covers the specifications of sensors developed by the authors to capture CPPG from prefrontal cortex.

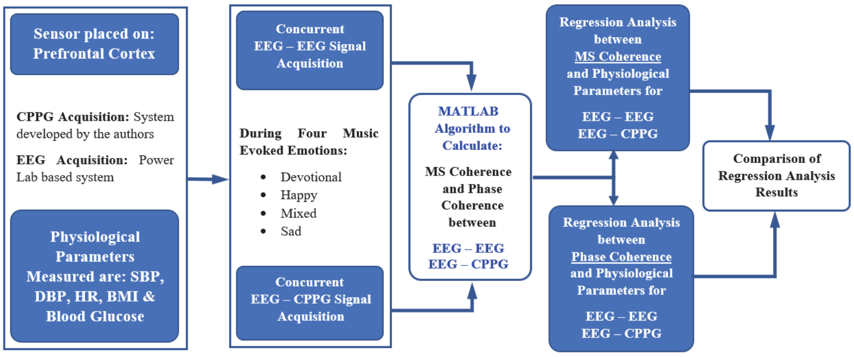

Fig. 2. System block diagram.

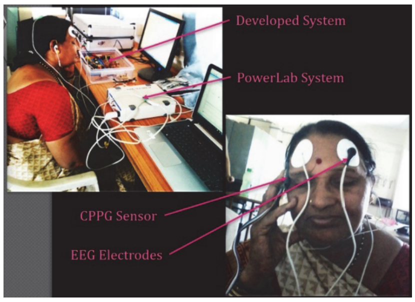

Fig. 3. System Setup for Congruent EEG – EEG and EEG – CPPG Signal acquisition during Music Evoked Emotions (EEG is captured using PowerLab based system and CPPG was captured using reflective type of sensor developed by the authors).

Table 2. Sensor specification [27].

Category	Specifications
Sensor	
Type	Reflection type of sensor
Source	860 nm (5 mm LED)
Detector	OPT 101 (Si Burr Brown diode)
Sensor Casing	Black Polyurethane
Optode Distance	1.5 cm
Supply	10V DC-Signal Conditioning Circuit; 5V, 2KHz AC to Source
Application	
Measurement Site	Anywhere on the human body from head to toe.

3. DATABASE COLLECTION DETAILS

EEG and CPPG data was recorded from Cummins College of Engineering for Women, for twenty healthy, right handed, multilingual, normal hearing, no history of neurological or psychiatric condition volunteer subjects, 8 males and 12 females, aged between 22 to 63 years. Statistical details of the database are as shown in Table 3. All the subjects gave verbal consent for using the biosignal related data and photos for the research purpose and publication. During the recording, the subjects were in the seated

Table 3. Statistical details of Physiological Parameters for the database used.

Physiological Parameters/ Statistical Parameters	Mean	Standard Deviation	Variance	Skewness	Kurtosis
Age (Years)	39.25	11.625	135.14	0.2555	–0.54
Blood Sugar (mg/dL)	117.05	39.53	156.25	2.27	6.01
Systolic BP (mm of Hg)	128.65	15.57	242.55	1.21	3.76
Diastolic BP (mm of Hg)	78	10.15	103.15	0.62	0.24
Heart Rate (bpm)	91	12.46	155.36	0.34	–0.64
Weight (Kg)	61.60	13.02	169.66	0.04	–0.16

position with eyes closed condition. For EEG – EEG, data acquisition was carried out by using a PowerLab with the sampling frequency of 250Hz. During data acquisition, four EEG electrodes were placed on prefrontal cortex in bipolar configuration and thus EEG was recorded on two channels concurrently. For EEG – CPPG, data acquisition of EEG was carried out by using a PowerLab and data acquisition of CPPG was carried out by using system developed by the authors. For each subject, data was acquired while listening to four 'Hindi' language songs with four emotions. All the subjects are multilingual and having depth of understanding of Hindi language up to reading and writing. Following are the four hindi songs used for the four music evoked emotions. Emotions for these songs were categorized by the song composer and they were accepted by the listeners in the same category.

- Devotional (D): Tu pyar ka sagar hai….Movie: Seema
- Happy (H): Aaj se Pehele, AAj se Jyada….Movie: Chit Chor
- Mixed (R): Mere Dholana….Movie: Bhool Bhulaiya
- Sad (S): Tuze Pata Hai Na Maa….Movie: Tare Zameen Par

4. RESULTS

Results section is divided into two parts. Part – I covers the regression analysis results for concurrent EEG – EEG signal captured from prefrontal cortex during music evoked emotions.

Table 4. Regression parameters for MS coherence between concurrent EEG – EEG signal and physiological parameters (SBP, DBP, HR, Blood Glucose, BMI) during four music evoked emotions.

Physiological Parameters	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
Systolic Blood Pressure	p-value	0.431	0.162	0.362	0.495
	% R^2	9.44%	19.26%	11.26%	7.95%
Diastolic Blood Pressure	p-value	0.597	0.638	0.129	0.452
	% R^2	5.89%	5.15%	21.40%	8.91%
Heart Rate	p-value	0.222	0.2	0.714	0.239
	% R^2	16.22%	17.27%	3.88%	15.48%
Blood Glucose	p-value	0.774	0.233	0.338	0.373
	% R^2	2.97%	15.74%	11.97%	10.96%
Body Mass Index	p-value	0.663	0.373	0.078	0.411
	% R^2	4.72%	10.97%	25.96%	9.93%

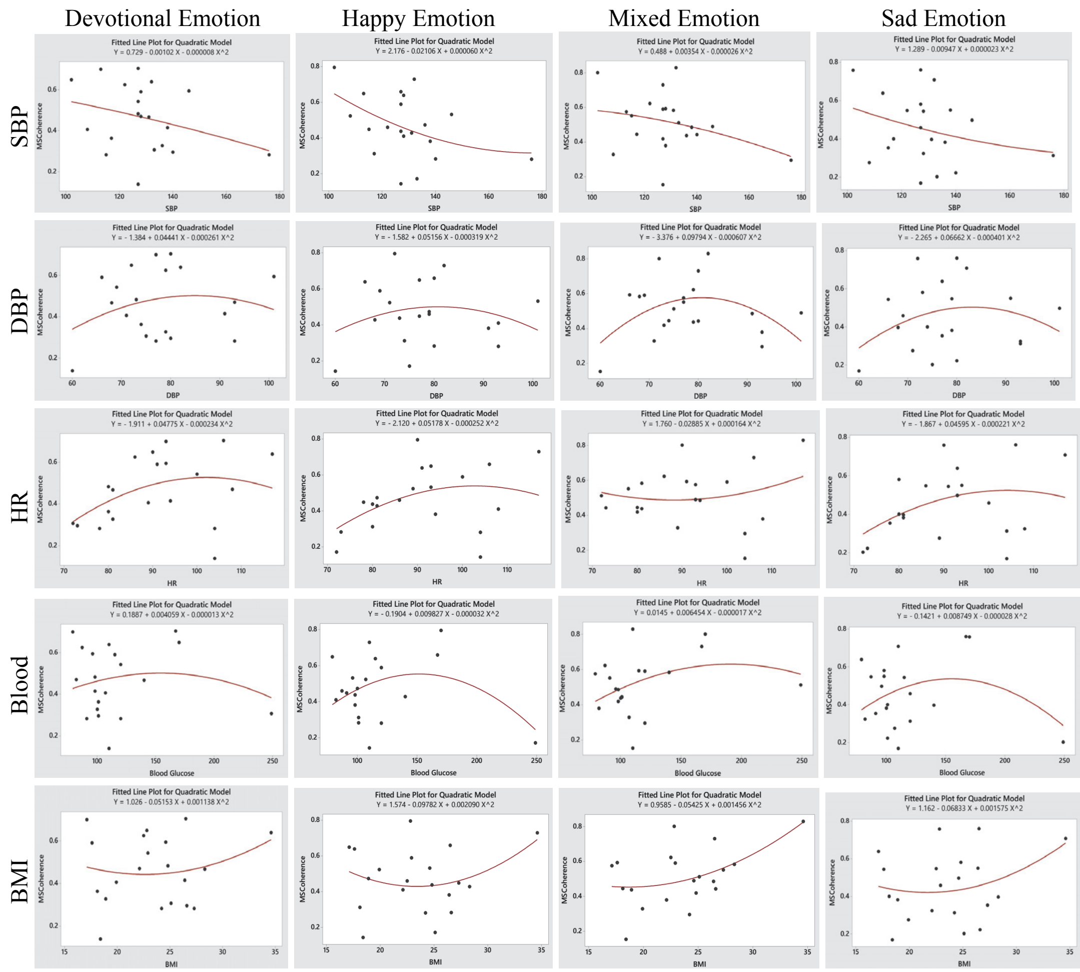

Fig. 4. Plot of quadratic regression model for MS coherence between concurrent EEG – EEG signal and physiological parameters during four music evoked emotions.

Table 5. Regression parameters for phase coherence between concurrent EEG – EEG signal and physiological parameters (SBP, DBP, HR, Blood Glucose, BMI) during four music evoked emotions.

Physiological Parameters	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
Systolic Blood Pressure	p-value	0.583	0.946	0.432	0.634
	% R^2	6.15%	0.65%	9.41%	5.22%
Diastolic Blood Pressure	p-value	0.366	0.443	0.811	0.716
	% R^2	11.14%	9.14%	2.44%	3.85%
Heart Rate	p-value	0.773	0.325	0.748	0.732
	% R^2	2.99%	12.38%	3.36%	3.60%
Blood Glucose	p-value	0.464	**0.001**	0.792	0.69
	% R^2	8.64%	**55.59%**	2.71%	4.27%
Body Mass Index	p-value	0.704	0.873	0.907	0.918
	% R^2	4.04%	1.58%	1.14%	1.00%

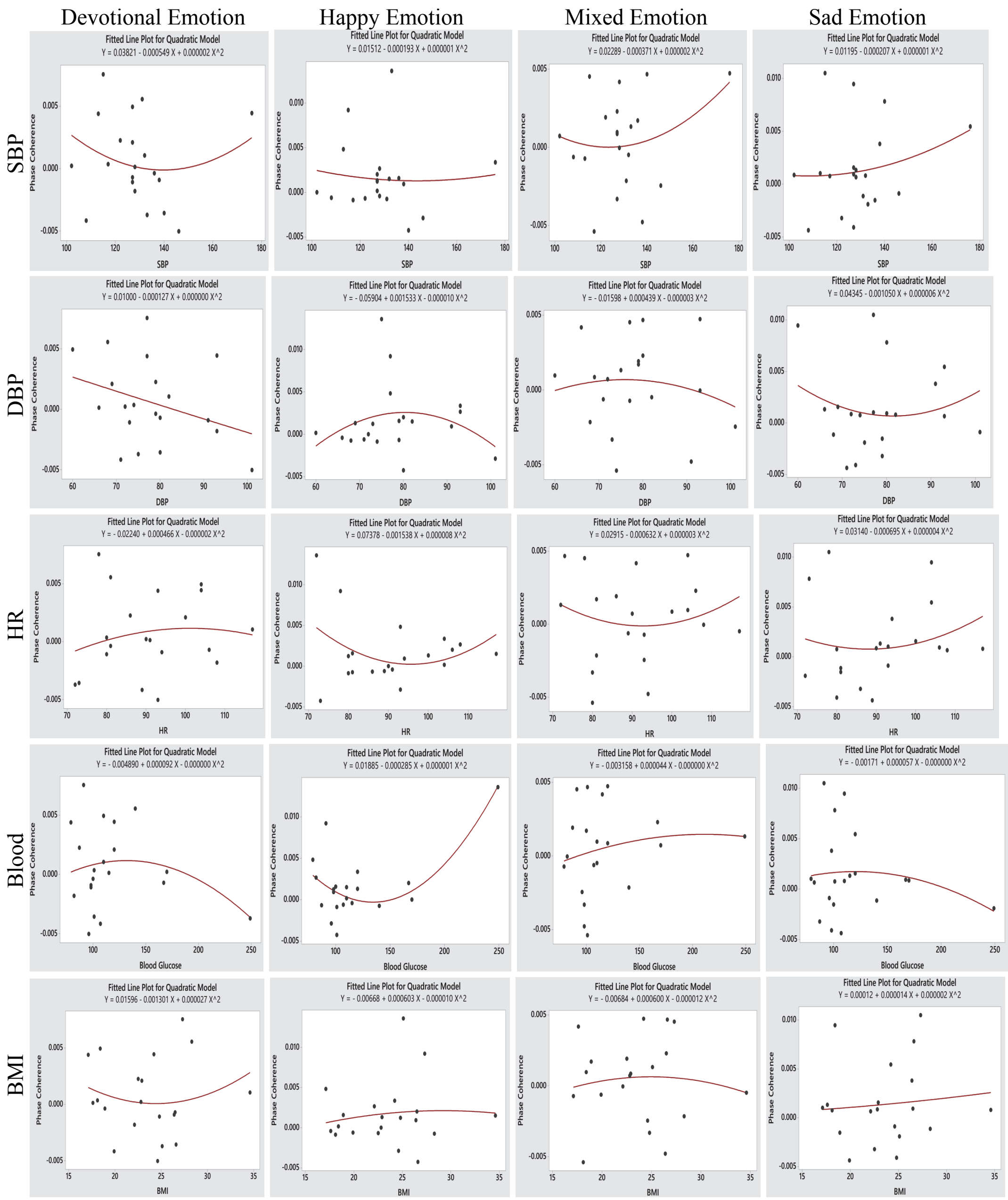

Fig. 5. Plot of quadratic regression model for phase coherence between concurrent EEG – EEG signal and physiological parameters during four music evoked emotions.

Part – II covers the regression analysis results for concurrent EEG – CPPG signal captured from prefrontal cortex during music evoked emotions.

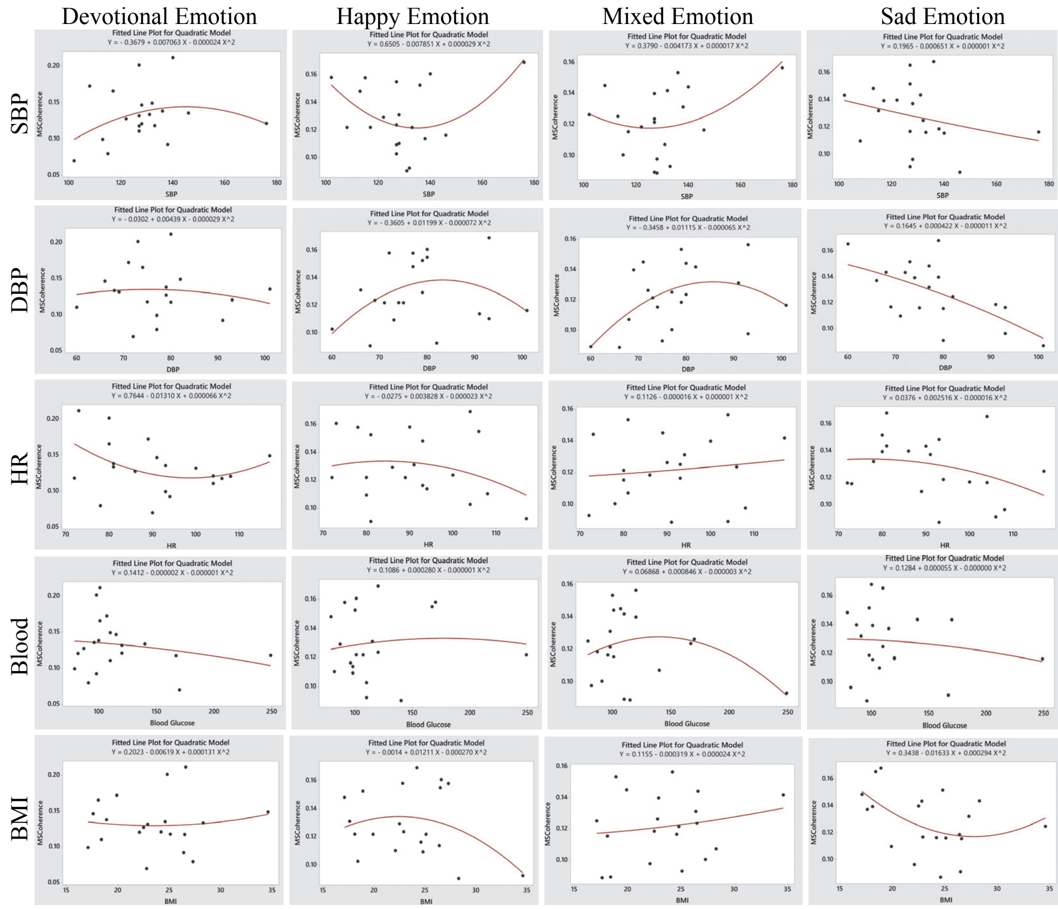

Fig. 6. Plot of quadratic regression model for MS coherence between concurrent EEG – CPPG signal and physiological parameters during four music evoked emotions.

Table 6. Regression parameters for MS coherence between concurrent EEG – CPPG signal and physiological parameters (SBP, DBP, HR, Blood Glucose, BMI) during four music evoked emotions.

Physiological Parameters	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
Systolic Blood Pressure	p-value	0.363	0.054	0.144	0.513
	% R^2	11.23%	29.06%	20.36%	7.55%
Diastolic Blood Pressure	p-value	0.852	0.202	0.093	**0.015**
	% R^2	1.87%	16.81%	24.37%	**38.95%**
Heart Rate	p-value	0.235	0.557	0.866	0.406
	% R^2	15.66%	6.66%	1.68%	10.05%
Blood Glucose	p-value	0.676	0.937	0.294	0.809
	% R^2	4.50%	0.76%	13.40%	2.46%
Body Mass Index	p-value	0.917	0.299	0.752	0.089
	% R^2	1.01%	13.25%	3.30%	24.81%

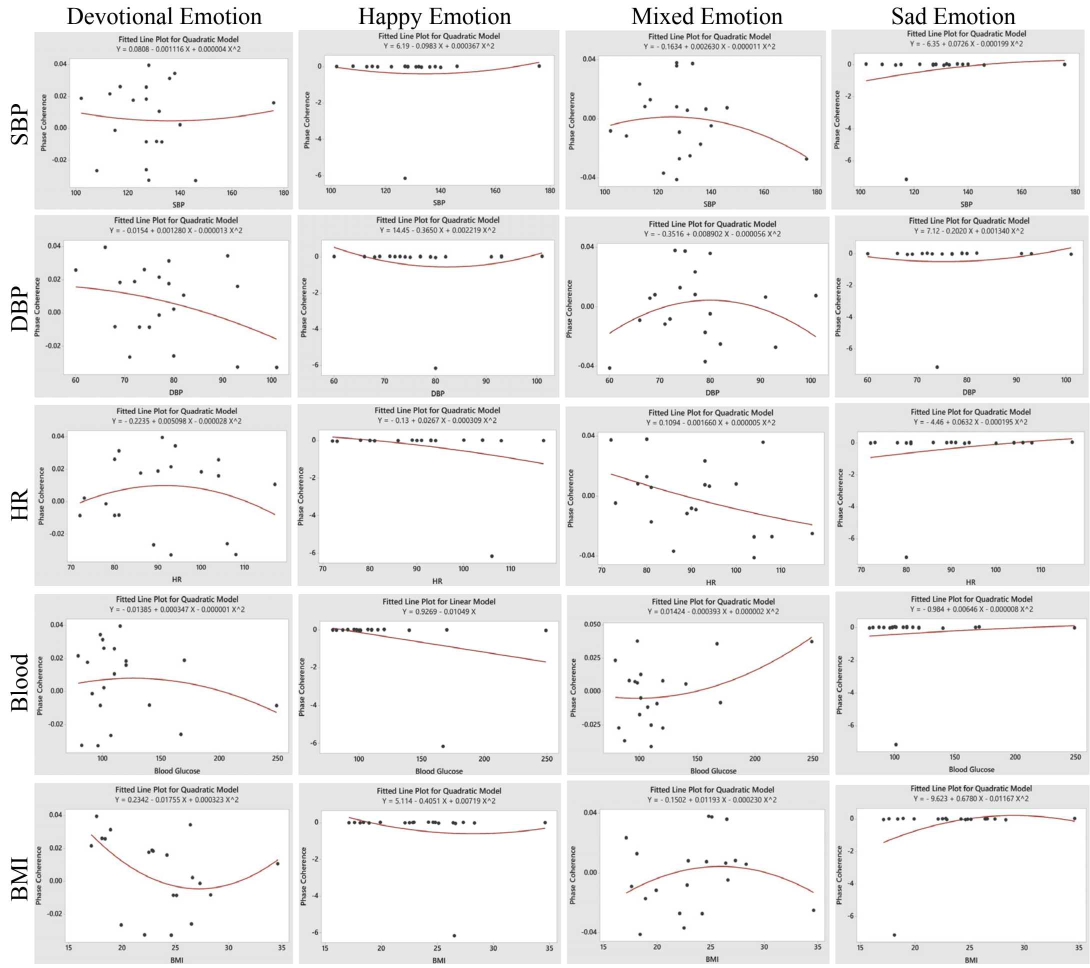

Fig. 7. Plot of quadratic regression model for phase coherence between concurrent EEG – CPPG signal and physiological parameters during four music evoked emotions.

Table 7. Regression parameters for phase coherence between concurrent EEG – CPPG signal and physiological parameters (SBP, DBP, HR, Blood Glucose, BMI) during four music evoked emotions.

Physiological Parameters	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
Systolic Blood Pressure	*p*-value	0.95	0.888	0.575	0.749
	% R^2	0.6%	1.39%	6.30%	3.34%
Diastolic Blood Pressure	*p*-value	0.328	0.687	0.458	0.844
	% R^2	12.29%	4.32%	8.78%	1.98%
Heart Rate	*p*-value	0.709	0.501	0.222	0.68
	% R^2	3.97%	7.81%	16.23%	4.44%
Blood Glucose	*p*-value	0.718	0.197	0.171	0.926
	% R^2	3.83%	9.05%	18.76%	0.90%
Body Mass Index	*p*-value	0.09	0.667	0.503	0.337
	% R^2	24.67%	4.66%	7.78%	12.00%

5. DISCUSSION

Estimation of magnitude and phase based synchronization between the two simultaneous acquired signals is given by magnitude squared coherence and phase coherence. Coherence based study of various biological signals is carried out by the number of authors in the recent years. Study was carried out mainly between the EEG-ECG signal or EEG-EEG signal. It was observed that the coherence estimated between the two same type of signals (*e.g.* EEG-EEG) is always higher than the coherence estimated between the two dissimilar signals (*e.g.* EEG-ECG). In this paper authors have carried out work on brain signals of similar nature (EEG-EEG) as well as brain signals with dissimilar nature (EEG-CPPG). MINITAB 17 based *T*-paired test was carried out to calculate *p*-value to support the above-mentioned statement. It was observed that the change in coherence based on psychological state is rarely studied by the research community. It was observed that the change in the coherence was prominent in the subjects with the various types of neuro-physiological disorders. To study the change in various brain/heart/muscular signals with respect to emotional states, estimation of more number connectivity measures (other than magnitude and phase coherence) can be studied.

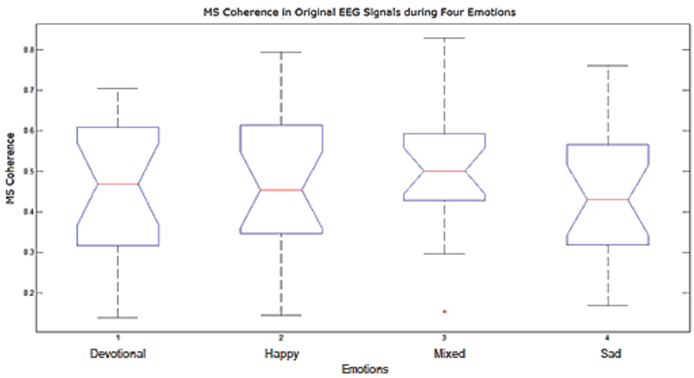

Fig. 8. Box plot of MS coherence between EEG-EEG during various emotions (Various Emotional States: D: Devotional; H: Happy; M: Mixed and S: Sad).

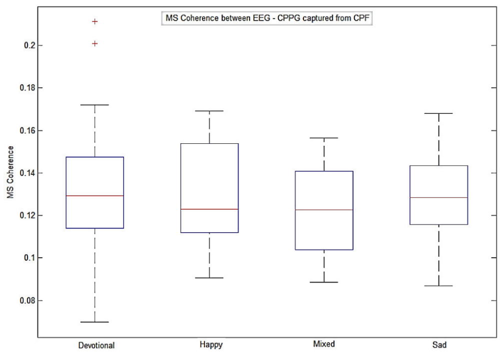

Fig. 9. Box plot of MS coherence between EEG-CPPG during various emotions (CPF: Central Prefrontal; LPF: Left Prefrontal; RPF: Right Prefrontal).

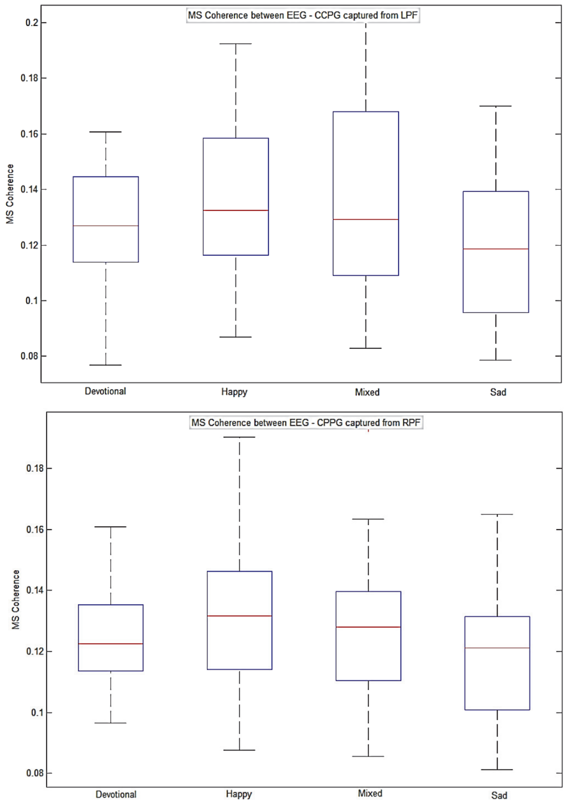

Fig. 9. (Cont'd) Box plot of MS coherence between EEG-CPPG during various emotions (CPF: Central Prefrontal; LPF: Left Prefrontal; RPF: Right Prefrontal).

Table 8. EEG-EEG concurrent modality: MS coherence and phase coherence.

EEG -EEG Concurrent Modality	MS Coherence		Phase Coherence	
Emotion	Mean	Standard Deviation	Mean	Standard Deviation
Neutral	0.4639	0.1626	0.0005	0.0034
Happy	0.4671	0.1770	0.0015	0.0039
Mixed	0.5132	0.1652	0.0003	0.0029
Sad	0.4542	0.1803	0.0013	0.0041

$P < 0.05$ means of two signals are significantly different. $P > 0.05$ means of two signals are not significantly different. CPPG signals captured from central prefrontal, left prefrontal and right prefrontal show least difference ($P > 0.05$) when they are compared based on MS Coherence. This shows that MS Coherence do not get affected with the position of the sensor on the prefrontal area. MS Coherence between EEG – CPPG at any emotional state on the prefrontal area so not vary. This shows that MS Coherence do not show difference in any specific emotional state; so, this feature is not good enough to reveal the difference in (to carry out the classification of) emotional states.

Table 9. *P*-value for *t*-paired test for MS coherence in EEG signal & CPPG signal at Central Prefrontal (CPF), Left Prefrontal (LPF) & Right Prefrontal (RPF).

Signal	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
EEG/EEG – EEG/CPF	*P*-value	< 0.001	< 0.001	< 0.001	< 0.001
EEG/EEG – EEG/LPF	*P*-value	< 0.001	< 0.001	< 0.001	< 0.001
EEG/EEG – EEG/RPF	*P*-value	< 0.001	< 0.001	< 0.001	< 0.001
EEG/CPF – EEG/LPF	*P*-value	0.578	0.494	0.081	0.297
EEG/CPF – EEG/RPF	*P*-value	0.393	0.729	0.467	0.268

Table 10. EEG-CPPG concurrent modality: MS coherence and phase coherence.

EEG-CPPG Concurrent Modality		MS Coherence		Phase Coherence	
	Emotion	Mean	Standard Deviation	Mean	Standard Deviation
Left Prefrontal	Neutral	0.1262	0.0232	–0.1648	1.8474
	Happy	0.1352	0.0296	0.3474	1.5726
	Mixed	0.1343	0.0327	–0.0578	0.2379
	Sad	0.1203	0.0266	–0.0213	1.5608
Central Prefrontal	Neutral	0.1318	0.0360	0.0058	0.0228
	Happy	0.1293	0.0237	–0.3013	1.3786
	Mixed	0.1217	0.0210	–0.0013	0.0238
	Sad	0.1279	0.0228	–0.3548	1.5996
Right Prefrontal	Neutral	0.1246	0.0159	0.4667	2.0820
	Happy	0.1319	0.0257	0.0033	0.0195
	Mixed	0.1275	0.0254	–0.5964	2.2487
	Sad	0.1199	0.0236	0.4026	1.7849

Phase coherence calculated between EEG-EEG and EEG-CPPG signal captured from prefrontal cortex during various music evoked emotions do not show any peculiar trend. This means phase coherence cannot be used as a feature for classification of emotions based on EEG CPPG two brain signals of similar or different nature. T-paired test was carried out using MINITAB 17 on phase coherence between EEG-EEG and EEG-CPPG signal.

Table 11. *P*-value for *t*-paired test for phase coherence in EEG signal & CPPG signal at Central Prefrontal (CPF), Left Prefrontal (LPF) & Right Prefrontal (RPF).

Signal	Parameters	Devotional Emotion	Happy Emotion	Mixed Emotion	Sad Emotion
EEG/EEG – EEG/CPF	*P*-value	0.289	0.338	0.765	0.332
EEG/EEG – EEG/LPF	*P*-value	0.694	0.338	0.287	0.949
EEG/EEG – EEG/RPF	*P*-value	0.329	0.692	0.250	0.327
EEG/CPF – EEG/LPF	*P*-value	0.685	0.170	0.316	0.512
EEG/CPF – EEG/RPF	*P*-value	0.334	0.336	0.251	0.163

6. LIMITATIONS

Every study carried out in the field of biomedical engineering has one or more limitations depending on the environment in which the study was carried out. Similarly, the study carried out by the authors do have some limitations such as: all the songs selected for inducing the emotions are in hindi language (National language of India). As the subjects are multi lingual, the songs can be from different languages known to the subjects and then the effect of change in MS Coherence and Phase Coherence with change in language can be studied. Similarly, only audio files of the songs are used to induce emotions. In future study can be carried out with audio visual songs for various emotions and more number of EEG channels can be studied and CPPG can be captured from other lobes of the brain. At the same time numbers of physiological parameters studied can be increased by including Respiratory Rate, EMG, Skin Conductance *etc.* Only coherence based study was carried out by the authors, in future more connectivity measures shown in table 1 can also be included to study EEG-CPPG signals during emotions.

7. CONCLUSION

CPPG is a hemodynamic brain signal generated because of change in blood volume (oxygenated and deoxygenated blood) and EEG is electrical brain signal genarated because of neuronal activity. Study of concurrent electroencephalogram and cranial photoplethysmogram was carried out by the authors. This study was divided into two parts. First part was concurrent acquisition of two electroencephalograms acquired from prefrontal cortex during various music evoked emotions. Second part was concurrent acquisition of electroencephalogram and cranial photoplethysmogram acquired from prefrontal cortex during various music evoked emotions. After concurrent acquisition mean square coherence and phase coherence was calculated between the concurrent EEG-EEG and EEG-CPPG brain signals. It was observed that the MS coherence between the signals with similar nature (EEG-EEG) is always higher than the MS coherence between the signals with dissimilar nature (EEG-CPPG). These values differ too much is shown by *p*-value obtained from MINITAB 17 based T-paired test. Conclusion is further divided into two parts: such as PART I: MS Coherence and Phase Coherence between concurrent EEG-EEG signals, PART II: MS Coherence and Phase Coherence between concurrent EEG-CPPG signals.

PART I: MS Coherence and Phase Coherence for EEG – EEG concurrent signal acquisition:

***Magnitude Square Coherence*:** SBP: No correlation was found between MS Coherence and SBP during various emotions (p value = 0.3625 ± 0.144, % R^2 = 11.98% ± 5.0%). DBP: No correlation was found between MS Coherence and DBP (p value = 0.454 ± 0.23, % R^2 = 10.34% ± 7.55%). HR: No correlation was found between MS Coherence and HR (p value = 0.3437 ± 0.2473, % R^2 = 13.21% ± 6.2%). Blood Glucose: No correlation was found between MS Coherence and Blood Glucose during various emotions (p value = 0.4295 ± 0.2372, % R^2 = 10.41% ± 5.36%). BMI: No correlation was found between MS Coherence and BMI (p value = 0.3812 ± 0.2396, % R^2 = 12.9% ± 9.1%). It was observed that the MS coherence between the two brain signals with similar nature are higher (0.4 to 0.5).

Phase Coherence: SBP: No correlation was found between Phase Coherence and SBP during various emotions (p value = 0.6487 ± 0.2159, % R^2 = 5.36% ± 3.6%). DBP: No correlation was found between Phase Coherence and DBP (p value = 0.584 ± 0.2131, % R^2 = 6.64% ± 4.1%). HR: No correlation was found between Phase Coherence and SBP (p value = 0.6445 ± 0.2136, % R^2 = 5.58% ± 4.5%). Blood Glucose: No correlation was found between Phase Coherence and SBP. Medium strong correlation between Blood Glucose and Phase Coherence was found during Happy Emotion ($p < 0.05$). BMI: No correlation was found between Phase Coherence and SBP (p value = 0.8505 ± 0.0995, % R^2 = 1.94% ± 1.4%). No variations in the quadratic regression model between Phase Coherence and SBP, DBP, HR, BMI, Blood Glucose was observed w.r.t. the various emotions. Very low positive phase coherence was observed between these two signals during all the four emotions.

PART II: MS Coherence and Phase Coherence for EEG – CPPG concurrent signal acquisition:

Magnitude Square Coherence: SBP: No correlation was found between MS Coherence and SBP during various emotions (p value = 0.2685 ± 0.208, % R^2 = 17.05% ± 9.65%). DBP: No correlation was found between MS Coherence and DBP (p value = 0.2905 ± 0.3821, % R^2 = 20.5% ± 15.44%). DBP and MS Coherence were found to be statistically significant ($p < 0.05$) during the SAD Emotion. HR: No correlation was found between MS Coherence and HR (p value = 0.516 ± 0.267, % R^2 = 8.51% ± 5.8%). Blood Glucose: No correlation was found between MS Coherence and Blood Glucose (p value = 0.678 ± 0.277, % R^2 = 5.28% ± 5.6%). BMI: No correlation was found between MS Coherence and BMI (p value = 0.5142 ± 0.3855, % R^2 = 10.59% ± 10.86%). Very weak correlation was observed between the BMI & MS Coherence during SAD Emotion. ($p > 0.05 \sim 0.08$) It was observed that the MS coherence between the two brain signals with dissimilar nature is very low (0.1).

Phase Coherence: SBP: No correlation was found between Phase Coherence and SBP during various emotions (p value = 0.7905 ± 0.1664, % R^2 = 2.91% ± 2.5%). DBP: No correlation was found between Phase Coherence and DBP (p value = 0.5792 ± 0.2306, % R^2 = 6.84% ± 4.5%). HR: No correlation was found between Phase Coherence and SBP (p value = 0.528 ± 0.2237, % R^2 = 8.11% ± 5.6%). Blood Glucose: No correlation was found between Phase Coherence and SBP. Medium strong correlation between Blood Glucose and Phase Coherence was found during Happy Emotion ($p < 0.05$) with average p value = 0.503 ± 0.3781 and % R^2 = 8.14% ± 7.8%. BMI: No correlation was found between Phase Coherence and SBP (p value = 0.3992 ± 0.2462, % R^2 = 12.28% ± 8.7%). No variations in the quadratic regression model between Phase Coherence and SBP, DBP, HR, BMI, Blood Glucose was observed w.r.t. the various emotions. Very low positive as well as negative phase coherence was observed between these two signals during all the four emotions.

No variations in the quadratic regression model between MS Coherence/Phase Coherence and SBP, DBP, HR, BMI, Phase Coherence, Blood Glucose was observed w.r.t. the various emotions. This shows that MS Coherence and Phase Coherence between the two concurrent EEG signals or EEG and CPPG concurrent signals should not be used as a feature for the classification of various emotions. Other connectivity measures can also be included to study the effect of various music evoked emotions on the brain signals captured from prefrontal cortex.

REFERENCES

1. V. Bono, D. Biswas, S. Das, and K. Maharatna, "Classifying human emotional states using wireless EEG based ERP and functional connectivity measures," in *Proceedings of IEEE-EMBS International Conference on Biomedical and Health Informatics*, 2016, pp. 200-203.
2. M. Balconi and M. E. Vanutelli, "Empathy in negative and positive interpersonal interactions. What is the relationship between central (EEG, fNIRS) and peripheral (Autonomic) neurophysiological responses," *Advances in Cognitive Psychology*, Vol. 13, 2017, pp. 105-120.
3. T. D. Dzhebrailova, I. I. Korobeinikova, N. A. Karatygin, and E. N. Dudnik, "Relationships between the EEG θ- and β-parameters and heart rate variability during human cognitive performance," *Human Physiology*, Vol. 43, 2017, pp. 199-212.
4. M. Teplan, A. Krakovská, and M. Špajdel, "Spectral EEG features of a short psycho-physiological relaxation," *Measurement Science Review*, Vol. 14, 2014, pp. 237-242.
5. K. Kallinen, "Towards a comprehensive theory of musical emotions – A multidimensional research approach and some empirical findings," *Jyvaskyla Studies in Humanities*, Vol. 50, 2006.
6. E. Jovanov, *Consciousness*, *Scientific Challenge of 21st Century*, United Nations, 1998.
7. P. Grosse, M. J. Cassidy, and P. Brown, "EEG-EMG, MEG-EMG and EMG-EMG frequency analysis: physiological principles and clinical applications," *Clinical Neurophysiology*, Vol. 113, 2002, pp. 1523-1531.
8. G. Giannakakis, D. Grigoriadis, and M. Tsiknakis, "Detection of stress/anxiety state from EEG features during video watching," in *Proceedings of Annual IEEE International Conference on Engineering in Medicine and Biology Society*, 2015.
9. C. Kaurand and P. Singh, "EEG derived neuronal dynamics during meditation: Progress and challenges," *Advances in Preventive Medicine*, Vol. 2015, Article ID 614723, 10 pages.
10. L. R. M. de Paiva, A. A. Pereira, M. F. S. de Almeida, G. L. Cavalheiro, S. T. Milagre, and A. de O. Andrade, "Analysis of the relationship between EEG signal and aging through linear discriminant analysis (LDA)," *Revista Brasileira de Engenharia Biomédica*, Vol. 28, 2012, pp. 155-168.
11. M. Beresford, A. Jedrczak, M. Toomey, and G. Clements, "EEG coherence, age-related psychological variables, and the transcendental meditation and TM-Sidhi programme," *Scientific Research on the Transcendental Meditation and TM-Sidhi Programme*, Vol. 3, 1983, pp. 1743-1748.
12. D.-K. Kim, K.-M. Lee, J. Kim, M.-C. Whang, and S. W. Kang, "Dynamic correlation between heart and brain rhythm during autogenic meditation," *Frontiers in*

Human Neuroscience, Vol. 7, 2013, p. 414.
13. L. M. Talamini, L. F. Bringmann, M. de Boer, and W. F. Hofman, "Sleeping worries away or worrying away sleep? Physiological evidence on sleep-emotion interactions," *PLoS ONE*, Vol. 8, 2013, e62480.
14. G. Singh, V. Gupta, and D. Singh, "Coherence analysis between ECG signal and EEG signal," *International Journal of Electronics and Communication Technology*, Vol. 1, 2010, pp. 25-28.
15. A. P. Kulaichev, "The informativeness of coherence analysis in EEG studies," *Neuroscience and Behavioral Physiology*, Vol. 41, 2011, pp 321-328.
16. R. Jerath and M. W. Crawford, "How does the body affect the mind? Role of cardiorespiratory coherence in the spectrum of emotions," *Advances Journal*, Vol. 29, 2015, pp. 4-16.
17. S. Chandra, G. Sharma, A. Z. Rizvi, N. Gupta, and A. P. Mittal, "Gender differences with different emotions for brain functional connectivity analysis," *International Journal of Scientific Research in Information Systems and Engineering*, Vol. 2, 2016.
18. L. Sebastiani, A. Simoni, A. Gemignani, B. Ghelarducci, and E. L. Santarcangelo, "Autonomic and EEG correlates of emotional imagery in subjects with different hypnotic susceptibility," *Brain Research Bulletin*, Vol. 60, 2003, pp. 151-160.
19. Y.-Y. Lee and S. Hsieh, "Classifying different emotional states by means of EEG based functional connectivity patterns," *PLoS ONE*, Vol. 9, 2014, p. e95415.
20. F. Nagel, "Psychoacoustical and psychophysiological correlates of the emotional impact and the perception of music," Institute of Music Physiology and Musicians' Medicine, Hannover University Music and Drama, Centre for Systems Neuroscience, Hannover, Germany, 2007.
21. S. Unde and R. Shriram, "Coherence analysis of EEG signal using power spectral density," in *Proceedings of the 4th International Conference on Communication Systems and Network Technologies*, 2014.
22. A. K. Golińska, "Coherence function in biomedical signal processing: a short review of applications in neurology, cardiology and gynaecology," *Studies in Logic*, *Grammar and Rhetoric*, Vol. 25, 2011, pp. 73-82.
23. R. Shriram, M. Sundhararajan, and N. Daimiwal, "Brain connectivity analysis methods for better understanding of coupling," *International Journal of Computer Science and Information Security*, Vol. 10, 2012, No. 11.
24. R. Chai, M. R. Smith, T. N. Nguyen, S. H. Ling, A. J. Coutts, and H. T. Nguyen, "Comparing features extractors in EEG-based cognitive fatigue detection of demanding computer tasks," in *Proceedings of the 37th IEEE Annual International Conference of Engineering in Medicine and Biology Society*, 2015, pp. 7594-7597.
25. R. Shriram and M. Sundhararajan, "Coherence analysis of pressure pulse & photoplethysmogram at various sites," *International Journal of Applied Engineering Research*, Vol. 10, 2015, pp. 14959-14968.
26. S. Shete and R. Shriram, "Statistical feature based activity classification," *International Journal of Computer Applications*, Vol. 95, 2014.
27. R. Shriram, M. Sundhararajan, and N. Daimiwal, "Statistical analysis of pulse acquired from various body sites using piezoelectric and optical transducer," *International Journal of Control Theory and Applications*, Vol. 8, 2015, pp. 831-838.

Revati Shriram received her B.E. from Cummins College of Engineering for Women, Pune, India and M.S. from Rose Hulman Institute of Technology, Indiana, USA, in 1999 and 2002 respectively. She has received her Ph.D. degree in Electronics Engineering from Sathyabama University, Chennai, India in 2018. Her research interests include biomedical signal and image processing, sensor design.

V. Vijaya Baskar Institute of Science and Technology, Chennai, India. His research interests include underwater acoustics, embedded system, signal and image processing.

Betty Martin Institute of Science and Technology, Chennai, India. Her research interest includes electronics and instrumentation design, signal and image processing.

M. Sundhararajan worked as a Dean Research at Bharath Institute of Higher Education and Research, Chennai, India. His research interest includes signal and image processing.

Nivedita Daimiwal worked with Cummins College of Engineering for Women. Her research interests include biomedical instrumentation, biomedical signal and image processing.