Understanding Brain Network Stimulation for Emotion Analyzing Connectivity Feature Map from Electroencephalography

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***Abstract*—In understanding brain functioning by Electroencephalography (EEG), it is essential to be able to not only identify more active brain areas but also understand connectivity among different areas. The functional and efficient connectivity networks of the brain have been examined in this study by constructing a connectivity feature map (CFM) with four widely used connectivity methods from the Database for Emotion Analysis Using Physiological Signals (DEAP) emotional EEG data to research how this connectivity's patterns are influenced by emotion. According to the investigation results, emotions are mainly related to the parietal, central, and frontal regions. The parietal region is more responsible for emotion alteration among these three regions. Positive emotions are associated with more direct correlations and dependencies than negative ones. When experiencing negative emotions, the regions of the brain function more synchronously as well as there are less flow of information. Whether direct or inverse, there is less correlation between brain regions in the higher frequency band than in the lower frequency band. Higher frequencies are associated with increased dependence and directed information transfer between brain regions. Generally, the electrodes in the same lobe show stronger connectivity than those in different lobes. At a glance, the present study is a comprehensive analysis to understand brain network stimulation for emotion from EEG, and it significantly differs from the existing emotion recognition studies typically focused on recognition proficiency.**

Keywords*—Brain connectivity; connectivity feature map; electroencephalography; emotion

I. Introduction

Interaction between brain areas have been recognized as a critical ingredient needed to understand brain function. Neuroimaging techniques are valuable for studying how the brain processes human emotions and activities. Emotion research has received increased attention from cognitive scientists and neurobiologists in recent decades, owing to its importance in decision-making, well-being, mood, personality, and psychotic diseases [1]. Electroencephalography (EEG) is a neuroimaging method that uses its sensors in the brain to record the electrical impulses generated by neural activity (i.e., electrodes or channels) affixed to the brain; it captures the changes in voltage brought on by ionic current flows in the neurons of the brain [2], [3], [4]. Recently, EEG has become popular for studying the brain's responses to emotional stimuli for its superior temporal resolution, noninvasiveness, portability, ease of use, and reasonably affordable speed [4], [5]. EEG is a composite signal that is composed of sub-bands such as Alpha (8–12 Hz), Beta (13–29 Hz), and Gamma (30–50 Hz) [6]. These sub-bands may provide a more accurate representation of the constituent neural process activity [7]. Connectivity features from the EEG signal can provide valuable information regarding brain connectivity behind emotion as these features analyze the interaction between different brain areas.

Several methods can measure the connectivity among EEG signals from different brain regions. Examples of such methods include Pearson correlation coefficient (PCC) [8], cross-correlation (XCOR) [9], phase locking value (PLV) [10], mutual information (MI) [11], normalized MI (NMI) [12], partial mutual information (PMI) [13], and transfer entropy (TE) [14]. PCC and XCOR are linear functional connectivity methods which can only detect linear dependencies between two signals or variables; PLV is nonlinear functional connectivity that represents the phase synchronization between two signals or variables. MI is nonlinear functional connectivity method, which measures the amount of shared information, whereas TE stands for effective nonlinear connectivity, which measures the directional flow of information between two brain regions. MI and TE are information-theoretic measures based on Shannon entropy [15]. Both NMI and PMI are two variants of MI. Such methods can be applied to signals collected through EEG electrodes to extract the connectivity features of the signals. The extracted features can be mapped into a two-dimensional matrix called a connectivity feature map (CFM). Emotion recognition (ER) and investigating brain mechanisms from CFM have become popular recently in the field of emotion research [16]–[22].

This study aims to analyze and understand brain network connectivity stimulation for different emotions through CFM from EEG, overcoming the limitations of the existing studies. The existing studies mainly focused on ER, and a few studies considered to investigate the brain mechanism behind/along ER. This study considers diverse connectivity methods for CFM construction and analysis to understand brain network stimulation emotion. Four frequently used connectivity methods, PCC, PLV, MI, and TE, were chosen. This study investigates connectivity represented in three sub-frequency bands named Alpha, Beta, and Gamma. Extensive studies using the developed CFMs have been conducted on the DEAP benchmark EEG dataset. An overview of the primary contributions of this work is provided below:

1) Brain network stimulation outcomes have been reviewed from existing studies.

2) Using four diverse, widely used connectivity methods, PCC, PLV, MI, and TE, CFMs are constructed for the DEAP dataset.

3) Distinctive and rigorous analysis of CFMs has been conducted to unveil discerning remarks on brain network connectivity levels (weak/strong) concerning stimulation for emotions with the frequency bands and brain lobes.

4) This study's findings are contrasted with those of comparable state-of-the-art research and identified novelty of the study.

The rest of this study is structured as follows. Section II briefly reviews prominent ER studies emphasizing brain network connectivity stimulation. The methodology to investigate brain mechanisms from CFM is described in Section III. Section IV presents the findings by analyzing CFM using the DEAP dataset. Section V presents a comparative discussion of the findings of the present study with related existing studies. At last, Section VI concludes the paper with a few remarks.

II. Literature Review

Emotion is the basic characteristic of human beings, and the brain is the root of emotion exposure. Emotion recognition (ER) analyzing EEG signals is well-studied in a number of existing studies. Proficiency of ER from EEG is the common main goal of those studies; however, several studies slightly focused on understanding brain network connectivity stimulation for different emotions and emotional states through CFM from EEG. The existing studies may be categorized under findings with respect to (w.r.t.) emotional states, brain regions, and frequency bands. The ensuing subsections provide a concise overview of notable ER research categorically.

A. Investigation Concerning Frequency Bands

The effect of different frequency bands on brain connectivity was investigated in a few studies [23], [24]. Li et al. [23], extracted the PLV feature and fused it with several other individual channel features; the fused feature was then classified by stacking an ensemble learning framework for ER. Brain function was also investigated with PLV feature under Theta, Alpha, Beta, and Gamma sub-frequency bands, from where it was identified that the PLV of the lower frequency bands (i.e., Theta and Alpha) is greater than those of higher frequency bands (i.e., Beta and Gamma). The same sub-frequency bands and PLV feature were also used by Cui et al. [24], to classify emotion and to analyze brain connectivity; they drew some conclusions that the Beta band has the lowest PLV, whereas the Theta band's PLV is significantly higher than other bands'.

B. Investigation Concerning Emotional States

Brain mechanisms concerning different emotions, such as positive and negative, have been investigated in several studies [12], [20], [21], [22], [17], [25]. Wang et al. [12], used NMI as a connectivity method to construct CFM. The aim of the study [12] was channel selection, where emotion classification was done with a support vector machine (SVM); the study also drew some conclusions on brain function behind emotion from where it was identified that the high Arousal low Valence state was found to have a wider active brain areas. Khosrowabadi et al. [20], used MI and another functional connectivity feature named magnitude MI and squared coherence estimate (MMSCE) to recognize emotion with SVM and K-nearest neighbor (KNN) classifier; they identified that various emotional states are accompanied by various types of functional brain connectivity. Liu et al. [21], performed emotion classification with the Xception network where brain mechanism also investigated with connectivity feature named coherence; the study found that the functional network made by low Valence-Arousal emotion revealed more active (i.e., higher coherence) functional connectivity than the one made by high Valence-Arousal emotion. When using the phase slope index (PSI) approach to study brain connectivity, Costa et al. [22], discovered a phenomenon whereby multi-channel EEG signals for sad emotions are more synchronized than those for happy emotions. Wang et al. [17], classified emotion with the PLV feature by Graph CNN; the PLV feature was also used to investigate brain connectivity. According to the study [17], the phase-locking value in the pleasant condition is lower than in the sad condition, which indicates that the pleasant mood is less active in the brain area. Recently, Wang et al. [25], identified from PLV feature that PLV values in positive emotions are generally smaller than in negative emotions; they also analyzed CFM concerning time periods and identified that there are little differences in connection patterns for the same emotions in different time periods.

C. Investigation Concerning Different Brain Regions

Several studies investigated responses of specific brain regions on different mental states by analyzing the CFMs with individual connectivity methods. Gao et al. [5], employed two effective connectivity features named TE and Granger causality (GC) for classifying stress and calm state with three classifiers (i.e., SVM, random forest, and decision tree); they highlighted from the GC that the parietal and frontal lobes show stronger connectivity during the stress state; and they also discovered from TE that there was a greater information exchange between the C4 and Fp1 channels under pressure. Chen et al. [8], used PCC, PLV, and TE feature methods to recognize emotion with domain adaptive residual convolutional neural network (CNN) as a classifier. Along with ER using the three feature methods, they investigated brain mechanisms through PCC and PLV features; it was found from CFM constructed with PCC that the brain's emotional activity is more perceptible in the occipital and parietal regions, and the CFM with PLV revealed that the phase consistency is relatively strong in the occipital, frontal and parietal regions, while the phase consistency is poor in other regions. For emotion recognition, Kong et al. [16], used sparse representation-based classification with connectivity feature PSI; the PSI method was also used for brain connectivity analysis from where it was found that, in sad emotion, the right prefrontal cortex (PFC) has stronger nodal connections than the left PFC, whereas, in happy emotion, the left PFC's nodal connection strength is stronger than the right PFC's. Graph CNN was used with the PLV feature by Wang et al. [15], to classify emotion under five sub-frequency bands (i.e., Delta, Theta, Alpha, Beta, and Gamma), but a single frequency band was used to investigate brain network and drew conclusions that emotions are related to mainly the temporal lobe. The study also showed that, during positive and negative emotions, the left and right forebrain generates strong EEG activity, respectively; the study shows that emotions are greatly correlated with the forebrain. Zhu et al. [18], used CNN to classify emotion with the phase lag index (PLI) feature and also explored phase synchronization of brain signals with that feature and found that, generally, the connectivity between the channels of the right frontal region was stronger than those of the left frontal region.

III. METHODOLOGY

In this study, connectivity is measured using different popular methods on the benchmark EEG dataset to understand brain network connectivity stimulation for emotion. Fig. 1 illustrates the framework of the proposed study; the EEG data preprocessing, CFMs construction using different connectivity methods, and analysis of the CFMs are the major steps of the study. The following subsections describe the EEG dataset and the connectivity methods to construct CFM.

A. Dataset Selection and Data Preprocessing

This study utilizes one of the most popular and well-studied EEG datasets for emotion detection, the Database for Emotion Analysis Using Physiological Signals (DEAP) [26]. In DEAP dataset development, 40 emotive music videos were utilized as stimuli on 32 individuals (i.e., subjects), and EEG and other peripheral physiological signals of individual subjects were collected as responses against individual videos. The database also includes subjective scores that describe the levels of Valence, Arousal, Liking, and Dominance of the emotional states produced by watching the videos. The preprocessed EEG signals from the database are used in this study, where the signal frequency range is 4.0 to 45.0 Hz. Of the 40 channels, 32 are used for EEG signals, and the remaining channels are used for peripheral physiological inputs. The ordering of the electrodes in the preprocessed version of the database is as follows: Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4, O2.

In the DEAP dataset, an EEG signal is 63 seconds long, and the first 3 seconds of data are the pre-trial baseline. By removing 3 seconds of pre-trial data, the remaining 60 seconds of data are processed for this study. For this investigation, a sliding time window of 8-second with a 4-second overlap is used to segment EEG data. Thus, there are 14 segments totaling 60 seconds. The total number of segments for each participant is 14 × 40 (video) × 32 (channel). EEGLAB [27] is used to filter the signal to extract Alpha, Beta, and Gamma sub-bands.

Among the four quality levels available in the DEAP dataset, Valence and Arousal are chosen in this study as they are well-studied scales for classifying emotions. In the dataset, the ratings for Valence and Arousal range from 1 (low) to 9 (high). Similar to the work in [28], Valence and Arousal are considered as high Valence (HV) and high Arousal (HA) for values above 4.5 and low Valence (LV) and low Arousal (LA) for less than or equal to 4.5. At a glance, HV indicates positive emotion, LV indicates negative emotion, HA indicates active emotion, and LA indicates passive emotion [29]. The positive and negative emotions or active and passive emotions can be represented in 2D space according to Russell's model [29], as shown in Fig. 2.

B. Connectivity Feature Map (CFM) Construction

Feature extraction has recently emerged in new dimensions through CFM construction using different connectivity measures [6]. This work takes into account several connectivity measures (linear, nonlinear, directed, etc.) for feature extraction as well as CFM creation. In a single experiment, the level of connectivity between two electrodes indicates the interaction between two brain areas. Depending on emotional or cognitive activities, this interaction could be a direct correlation, an inverse correlation, or synchronization. Four popular candidate connectivity methods were chosen from linear functional, nonlinear functional connectivity and nonlinear effective connectivity categories. The selected methods are PCC, PLV, MI, and TE.

The linear correlation between two signals, X and Y, is measured by PCC and is calculated as

$$PCC_{XY} = \frac{n\sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{n\sum X_i^2 - (\sum X_i)^2}\sqrt{n\sum Y_i^2 - (\sum Y_i)^2}}, \tag{1}$$

where, n denotes sample size, and X_i or Y_i is the individual sample points indexed with i. PCC's value varies from -1 to 1. (-1): complete linear inverse correlation, (0): no linear interdependence, (1): complete linear direct correlation between the two signals.

PLV defines the phase synchronization between two signals, which is measured by the rules as follows-

$$PLV(X,Y) = \frac{1}{T}\left|\sum_{t=1}^{T} exp\{j(\varphi_X^t - \varphi_Y^t)\}\right|, \tag{2}$$

where, φ^t denotes the phase of the signal at time t, X, and Y are two electrodes, and T is the length (time) of the signal. PLV has a value between 0 and 1, denoting perfect independence and perfect synchronization, respectively.

MI is an information theoretic approach to measuring shared information between two variables. The following is the definition of MI between two random variables, X and Y:

$$MI(X,Y) = H(X) + H(Y) - H(X,Y), \tag{3}$$

where, H denotes Shannon entropy [15]. Entropy is measured by calculating the probability using the fixed bin histogram approach. There are 10 bins utilized in the computation. The marginal entropies of the two variables X and Y are H(X) and H(Y), respectively, and their combined Entropy is $\mathrm{H(X,Y)}$. The range of MI's value is: $0 \leq \mathrm{MI(X,Y)} < \infty$. If $\mathrm{MI(X,Y)}$ is equal to 0, then X and Y are independent. If $\mathrm{MI(X,Y)}$ is greater than 0, then X and Y are dependent.

The directed information flow from a signal or time series Y to another signal X is measured by TE.

$$TE_{Y\rightarrow X} = H(X_t, Y_t) - H(X_{t+h}, X_t, Y_t) + H(X_{t+h}, Y_t) - H(X_t) \tag{4}$$

If the future of X, i.e., X_{t+h} is denoted by w, then transfer Entropy $TE_{Y\rightarrow X}$ can be computed as:

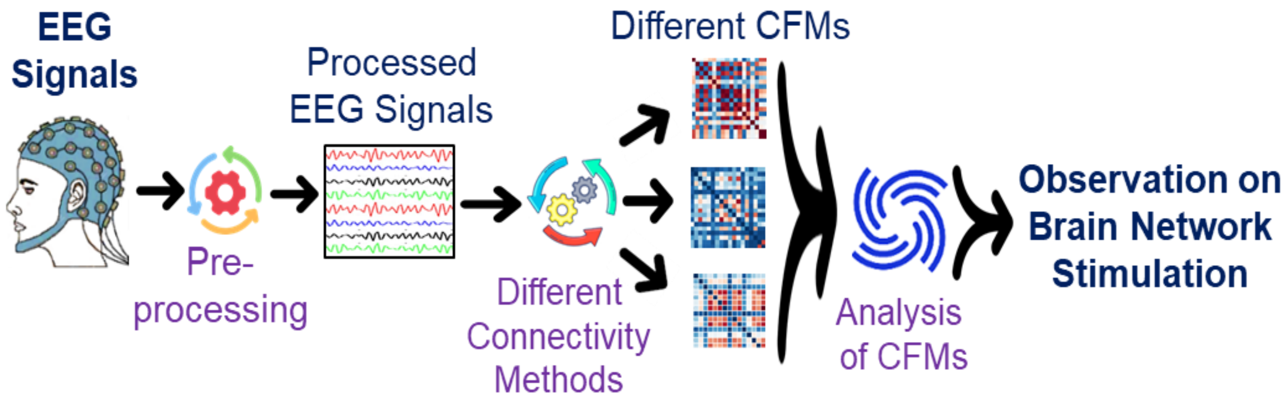


Fig. 1. The framework of the proposed study to observe brain network stimulation from EEG for emotion.

$$TE(w,X,Y) = H(w,X,) + H(X,Y) - H(X) - H(w,X,Y) \quad (5)$$

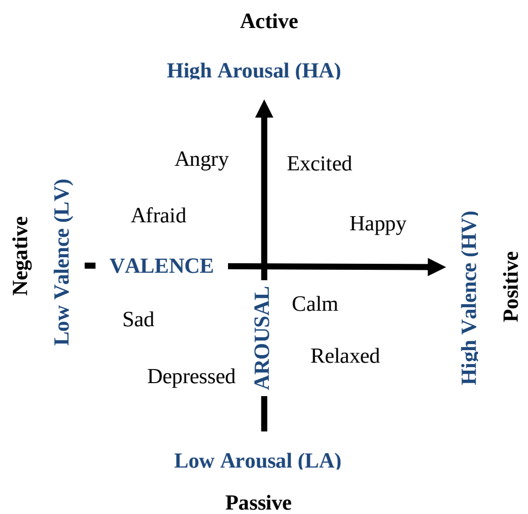


Fig. 2. Russell's emotion model.

The ranges of TE value are $0 \leq TE_{Y \to X} < \infty$. If the TE = 0, then there is no directed flow of information, i.e., no causal relationship between the signals. TE > 0 means that there is a causal relationship between them.

When it comes to CFM, these variables are signals from particular EEG channels. Connectivity features are extracted for each pair (X, Y) of EEG electrodes. The connectivity features extracted from all electrode pairs can be mapped into a matrix (i.e., CFM). The matrix element at (X, Y) describes the connectivity strength between the signals collected from the Xth and Yth electrodes. As the data are segmented in the preprocessing stage, a total of 17,920 CFMs are constructed under each frequency band for each connectivity method from all 32 participants, each with 40 trials.

IV. Results of CFM Analysis on Brain Network Stimulation for Emotion

CFM analysis for brain networks is the main contribution of this study to observe the connectivity depiction of emotion. The following subsections briefly describe brain network stimulation for emotion-analyzing CFM in different dimensions/directions. CFMs representation as heat maps is commonly available in the existing studies [6] that are followed in this study.

A. Effect of Sub-Bands on Emotion Analysis

The CFM created from the three frequency bands (i.e., Alpha, Beta, and Gamma) with the four connectivity methods (i.e., PCC, PLV, MI, and TE) under positive and negative emotions are displayed in Fig. 3. The response of the brain of a person to an emotion may be different from another person. Therefore, the constructed CFMs are presented for two individual participants (participant 1 and participant 32) as well as the average CFM of the total 32 participants.

It can be observed for PCC in Fig. 3(a) that, for participant 1, red and blue colors are lighter in the Gamma band, and the colors are darker in the Alpha band. The Beta band CFM colors remain in the middle of the two. In the case of Participant 2, the CFMs in the Beta band contain the lowest PCC value than that of the Alpha and Gamma bands. When the average CFM is considered, it can be observed that the correlation between brain regions, either a direct correlation or inverse correlation, is higher in the lower frequency band than in the higher frequency band, which is similar to Participant 1. As shown in Fig. 3(b), CFMs for both participants and the average CFMs, the Gamma band has a considerably larger PLV than the other bands, while the Beta band has the lowest. This implies that the Gamma frequency band had higher synchrony. In the case of MI in Fig. 3(c), the Beta band holds the highest MI value for Participant 1, and the Gamma band holds the highest MI value for Participant 32. When the CFMs from all participants are averaged, it is found that the mutual dependency between brain regions increases with higher frequency. Fig. 3(d) shows the CFMs constructed with TE, where it can be seen that with increased frequency, information flows more often between different parts of the brain.

Among the three frequency bands, the positive and the negative CFMs are more easily distinguishable in the Gamma frequency band. A number of studies have also identified that the Gamma band exhibits better emotional observation than the Alpha and Beta bands [19], [30]. So, further discussions in the next sections are presented with the average CFMs from the Gamma band only for concise observation.

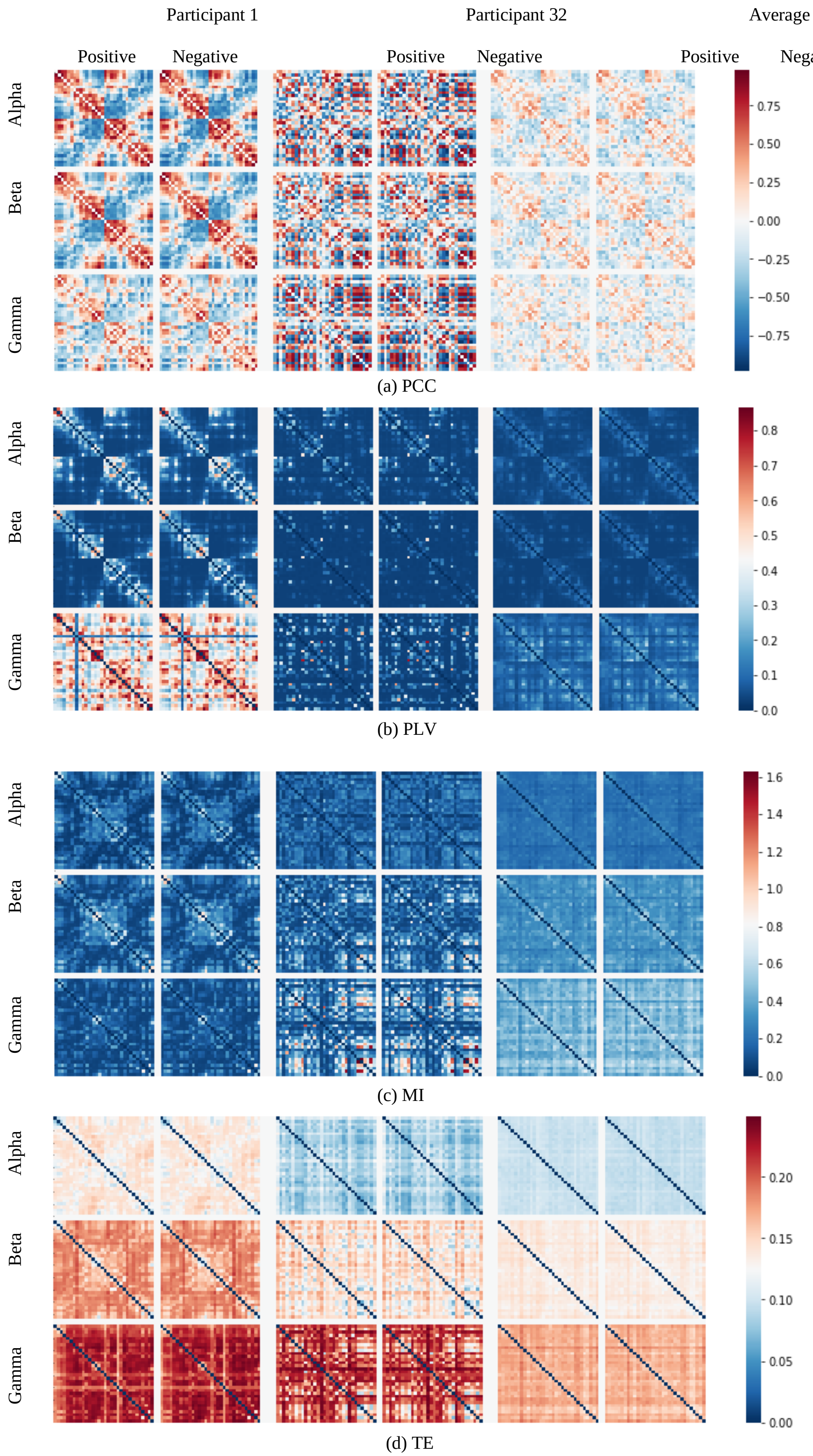


Fig. 3. CFM with different connectivity methods in alpha, beta, and gamma frequency bands for the positive and negative emotion.

B. Connectivity Strength in Positive and Negative Emotions

Connectivity methods offer useful information about brain connectivity behind emotions. As discussed in the previous section, high Valence emotions are regarded as positive emotions and low Valence emotions are regarded as negative emotions. Fig. 4 illustrates how changes in emotions affect two brain regions' correlation, phase synchronization, mutual dependence, as well as causal relationship. The linear correlation between two brain areas is measured by PCC. The PCC-constructed CFM for positive and negative emotions in the gamma band is displayed in Fig. 4(a). Negative PCC values (blue pixels of the figure) denote an inverse linear correlation between two areas of the brain, and positive PCC values (red pixels of the figure) denote a direct linear correlation. As can be shown from Fig. 4(a), there are more locations with a strongly inverse correlation for negative emotion than for positive emotion. As compared to the CFM of positive emotion, the blue pixels in Fig. 4(a) are darker when representing negative emotion. For better visualization, a few areas are marked with blue rectangles. It implies that during unpleasant emotions, there is a greater inverse correlation between brain regions. Positive CFM shows darker red pixels than negative CFM, indicating a more direct linear correlation between brain regions during positive emotion than during negative emotion. Such few areas are marked with red rectangles.

Phase synchronization between two brain areas is described by PLV. Two signals are totally independent when the PLV value is 0; synchronization between the signals is indicated when the PLV value is greater than 0, and perfect synchronization is indicated when the PLV value is equal to 1. The CFM built for both positive and negative emotions utilizing PLV in the gamma frequency range is displayed in Fig. 4(b). In the CFM, a large phase-locking value is represented by red pixels, and a lesser phase-locking value is represented by blue pixels. Positive emotions have a phase-locking value that is comparatively lower than negative emotions, as seen in Fig. 4(b). Such few areas are marked with red rectangles. Therefore, in the negative state, the phase synchronization of distinct brain areas is greater. The higher values show that the synergy between various brain regions is increased during negative emotions, which results in synchronous oscillations. It is thus considered that the human brain pays greater attention to details in negative emotions than in happy emotions.

Fig. 4(c) and Fig. 4(d) displays the CFMs created for positive and negative emotions employing MI and TE, respectively. The MI calculates how dependent the two areas of the brain are. The more dependent two brain regions are on one another, the higher the value of MI. Fig. 4(c) shows that when an individual experiences negative emotions, there is an increase in the dependency between different brain regions and this phenomenon can be easily observed through the red-marked area. TE quantifies the directed transfer of information across different regions of the brain. More information transfer between two different parts of the brain results in a higher score for TE. It is evident from Fig. 4(d) that the negative CFM pixels are lighter than the positive CFM pixels, which can be easily seen through the white rectangular area, suggesting that positive emotions have a greater directed information flow than negative emotions.

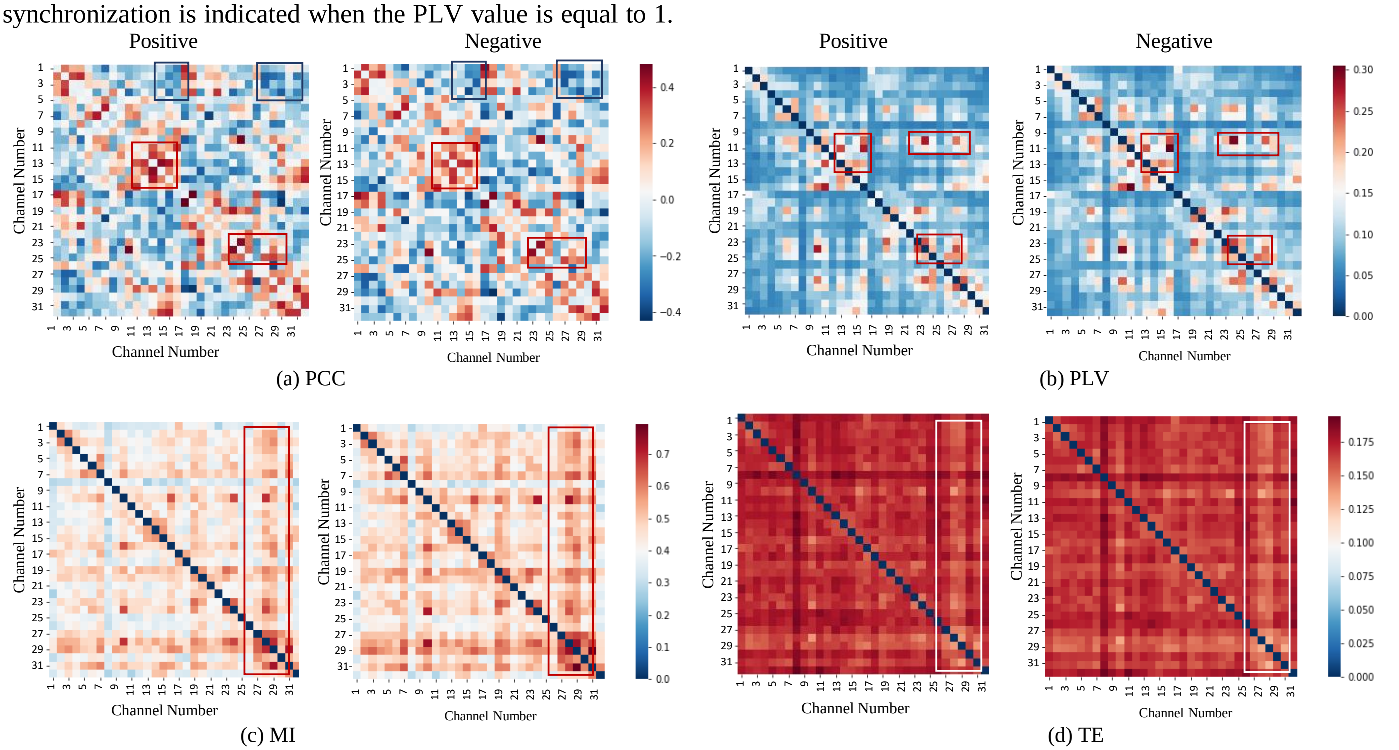


Fig. 4. CFM with different connectivity methods in Gamma band for the Positive (high Valence) and Negative (low Valence) emotions.

C. Brain Region Distinctiveness on Emotion

Observing the effects of stimulation in brain regions on emotional consequences by analyzing the CFMs with individual connectivity methods is interesting. Fig. 5 illustrates higher and lower brain connectivity regions based on the analysis performed in the previous section with Fig. 4. From the PCC connectivity matrix in Fig. 4(a), it is seen that signals from nearly placed electrodes are highly correlated both in positive and negative emotions. For example, electrodes 17 and 18 (i.e., Fp2, AF4), electrodes 13 and 14 (i.e., PO3 and O1), electrodes 23 and 24 (i.e., FC2 and Cz), and electrodes 10 and 24 (i.e., CP1 and Cz) are placed nearly in the scalp and the PCC value for each pair of the electrode are high. Similarly, from the PCC matrix, it is also observed that inversely correlated electrodes are located far away (e.g., AF4 and P4). The highly correlated electrodes are marked in Fig. 5(a), where red lines indicate higher direct correlations and the blue line indicates higher inverse correlation.

Fig. 4(b) (for PLV) shows that the degree of some electrodes is noticeably higher than that of other electrodes. This means that some brain regions with higher degree electrodes may be in charge of producing specific emotions since they are more involved and synchronized with other brain regions. After summing all the PLV values for individual electrodes, it is found that both Positive and Negative CFM in Fig. 4(b), electrode 16 (i.e., Pz) holds the highest PLV value in the matrix, and the second highest value contains electrode 10 (i.e., CP1). Visual inspection of the figure also proves this. The third highest value contains electrodes 28 and 11 (i.e., CP2 and P3) in Positive and Negative CFM, respectively. The fourth highest value contains electrodes 11 and 28 (i.e., P3 and CP2) in Positive and Negative CFM, respectively. As mentioned, all the electrodes are in the parietal lobe; from here, it can be concluded that emotions are mainly related to the parietal lobe. The overall less synchronization can be seen with the electrodes 1, 8, 12, 13, 17, 18, 21, 26, and 30 (i.e., Fp1, T7, O1, P7, Fp2, AF4, F8, T8, and P8), which are located far from the electrode Cz or the center of the scalp. The distinction between positive and negative emotion can be easily seen through electrodes 10, 11, 16, and 27 (i.e., CP1, P3, Pz, and CP6), which means the parietal lobe is more sensitive to emotion alteration. The electrodes having higher and lower PLV values are marked in Fig. 5(b), where red highlights indicate higher PLV value and blue highlights indicate lower PLV value.

Similarly, from the MI connectivity matrix in Fig. 4(c), it can be observed that electrodes in parietal, central, and frontal regions such as C3, CP1, Pz, Fz, CP2, P4, and PO4 (i.e., 7, 10, 16, 19, 28, 29 and 31) hold higher MI values. The electrodes are marked in Fig. 5(c). The color variances between positive and negative CFM can also be easily seen through these electrodes, which indicates these brain regions are more sensitive to emotion alteration. Most of the electrodes, as mentioned above, are from the parietal lobe, i.e., among these three regions, the parietal region is more responsible for altering emotion.

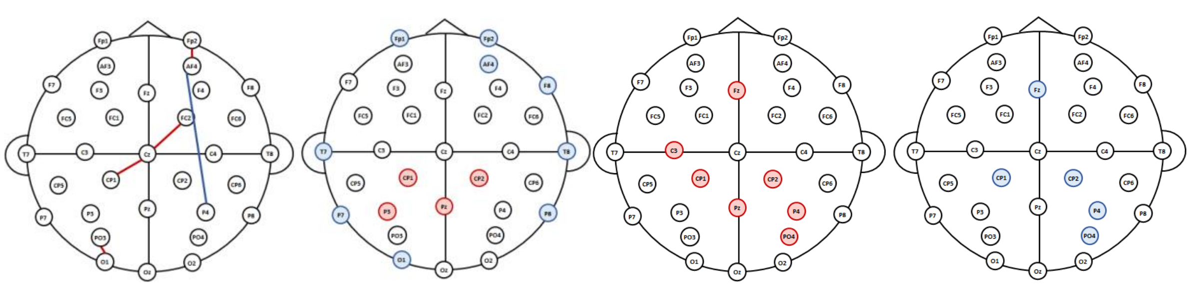
Section III(B) discusses that variation in CFM values of positive and negative emotion are opposite for MI and TE; positive CFM contains lower MI values and higher TE values. This phenomenon can be easily observed through the parietal, central, and frontal region's electrodes CP2, P4, Fz, PO4, and CP1 (i.e., electrodes 28, 29, 19, 31, and 10) in Fig. 4(d), which contain lower TE values. The electrodes are also marked in Fig. 5(d).

The findings from the CFM of the Gamma band discussed in Sections III(B) and III(C) are also satisfied by the Alpha and Beta band's CFM in Fig. 3, although the Gamma band's CFMs are easily observable. From all the CFM, it is also identified that, in general, the electrodes located in the same lobe show stronger connectivity than the electrodes located in different lobes.

D. Connectivity Strength in Active and Passive Emotions

As discussed in the previous section, high Arousal (HA) emotions are regarded as active emotions and low Arousal (LA) emotions are regarded as passive emotions. Fig. 6 shows how correlation [Fig. 6(a)], phase synchronization [Fig. 6(b)], mutual dependency [Fig. 6(c)], and causal relationship [Fig. 6(d)] between two brain regions change with the changes in intensity (levels of Arousal) of emotions. These are the average CFMs created from the Gamma frequency band under active and passive emotions. From Fig. 6(a), it can be seen that the red pixels are darker in passive emotions, i.e., a more direct correlation exists in passive emotions. The blue pixels are darker in active emotions, i.e., a more inverse correlation exists in active emotion. The phase synchronization between brain regions under active and passive emotions can be observed in Fig. 6(b). Lower PLV values exist in active emotions. The red pixels are darker, and the blue pixels are lighter in passive emotion, i.e., the higher phase synchronization can be seen in passive emotion. The higher MI values and lower TE values are observed in active emotions than in passive emotions.

Similar to the Fig. 4, Fig. 6 also revealed that the emotions are mainly related to the parietal, central, and frontal regions, among which the parietal region is more responsible for emotion alteration.



(a) PCC (b) PLV (c) MI (d) TE

Fig. 5. Visualizing higher and lower brain connectivity regions.

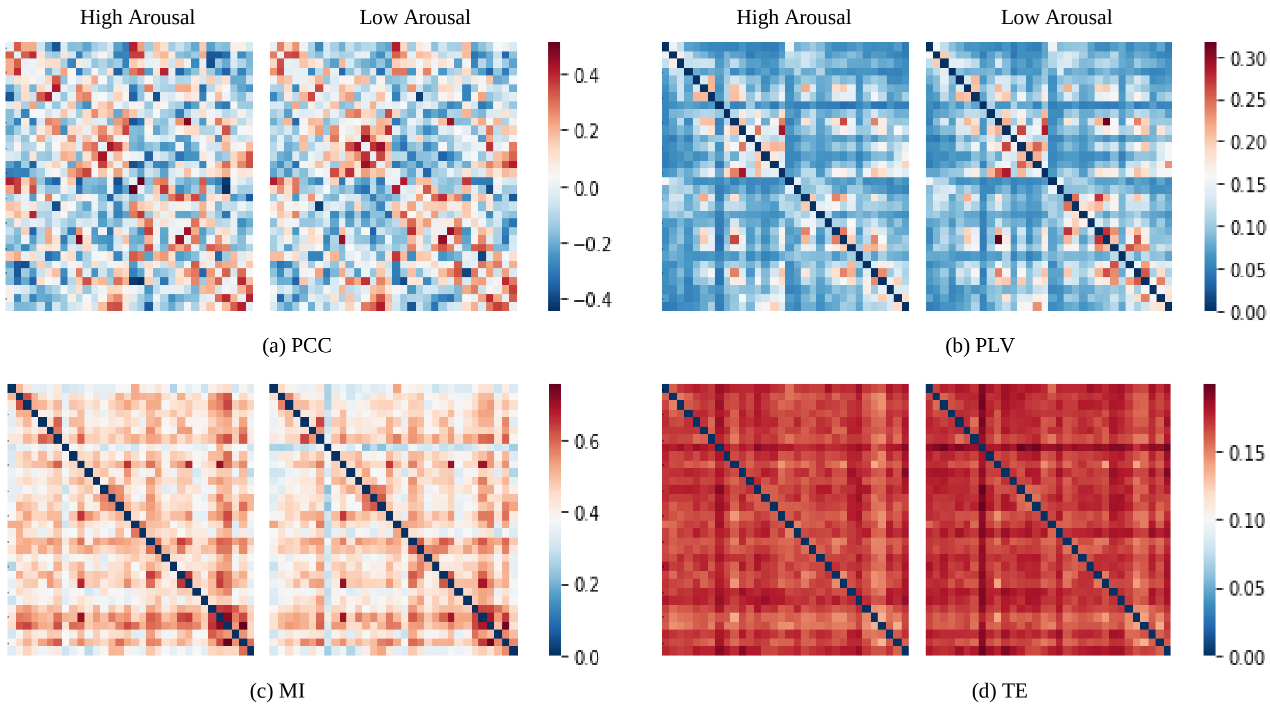


Fig. 6. CFM with different connectivity methods in Gamma bands for the Active (high Arousal) and Passive (low Arousal) Emotions.

V. Comparison with other Studies

This section briefly compares different findings with different connectivity methods achieved in different studies with respect to the findings of this study. Table I summarizes the specific findings from different existing studies under three major categories: findings with respect to (w.r.t.) frequency bands, emotional states, and brain regions. It is observed from the table that all the existing methods, except [5], [8], and [20], considered a single connectivity method (e.g., PCC, PLV) in their studies. Moreover, an existing method is limited to performing findings in a particular category, such as brain regions. On the other hand, present studies considered four connectivity methods for all three categories. Therefore, the findings of this study are much more pervasive than existing studies.

The present study and the study [23] and [24] investigated CFM constructed with PLV under different frequency bands. All three studies found that the Beta band has the lowest synchrony, i.e., the lowest PLV value. Between the Alpha and Gamma bands, the study [22] found that the PLV value of the Gamma band is higher than the PLV value of the Alpha band, but according to the study [21], the PLV value of the Alpha band is higher than the PLV value of Gamma band. The result of the present study is similar to the study [24]. Apart from the existing research, this study has also found that a higher correlation (i.e., PCC value) between brain regions exists in the lower frequency band than in the higher frequency band. The mutual dependency (i.e., MI value) between brain regions and the flow of information (i.e., TE value) from one brain region to another brain region increases with higher frequency. Several studies investigated CFM for positive vs. negative emotion and active vs. passive emotion with PLV [23], PSI [20], MI [18], etc. In addition to their findings, few new findings appeared from the current study. This study has found that a more direct correlation between brain regions exists in passive emotion, and a more inverse correlation exists in active emotion. The amount of directional flow of information is lower in active emotion than that of passive emotion. The present study has found that the parietal region is more responsible for emotion alteration than the other regions, while the study [17] found the temporal region as more responsible for emotion alteration, and the study [8] found that parietal as well as occipital regions are more responsive to the brain's emotional activity.

TABLE I COMPARISON FINDINGS WITH OTHER STUDIES

Ref.	Connection Method	Major Category	Specific Findings
[23]	PLV	Findings w.r.t. Frequency Bands	The PLV of the lower frequency bands (i.e., Theta and Alpha) is greater than those of higher frequency bands (i.e., Beta and Gamma).
[24]	PLV		1. Compared to other bands, the PLV of the Theta band is significantly higher. 2. The lowest PLV is seen in the Beta band.
[24]	PLV	Findings w.r.t. Emotional States	1. In the HA state, each frequency band has a higher PLV than in the LA state. 2. In the HV state, the PLV is lower than in the LV state in all frequency bands.
[25]	PLV		1. PLV values in positive emotions are generally smaller than in the negative emotions 2. There are little differences in connection pattern for same emotion in different time periods.
[17]	PLV		PLV value in the pleasant mood is lower than in the sad mood, i.e., pleasant mood is less active in the brain area.
[20]	MMSCE, MI		There are distinct types of functional brain connections associated with various emotional states.
[21]	Coherence		Higher Coherence induced by low Valence-Arousal emotion.
[22]	PSI		Signals in sad emotion are highly synchronized than those in happy emotion.
[12]	NMI		A broader range of activated brain regions exists in the high Arousal low Valence state.
[5]	GC, TE	Findings w.r.t. Brain Regions	1. The parietal and frontal lobes show stronger connectivity during the stress state. 2. Higher TE value between Fp1 and C4 channels is found under pressure.
[8]	PCC, PLV		1. There are stronger correlations between the left and right frontal areas of the brain. 2. Frontal lobe area's connectivity is supportive for emotion recognition. 3. Parietal as well as occipital regions are more responsive to the emotional activity. 4. There is enhanced synergy between the brain's occipital and left frontal regions. 5. Phase consistency in the parietal, frontal and occipital regions is relatively stronger than in the other regions.
[16]	PSI		1. In sad state, nodal connection strength in right PFC is higher than that in left PFC. 2. In happy state, nodal connection strength in left PFC is higher than that in right PFC.
[17]	PLV		1. Positive and negative moods produce strong connectivity in the left and right forebrain, respectively. 2. Emotions are related mainly to the temporal lobe of the human brain.
[18]	PLI		Generally, the right frontal region's channels often have stronger connective strengths than the left frontal region's.
This Study	PCC, PLV, MI, TE	Findings w.r.t. Frequency Bands	1. Gamma bands have higher synchrony whereas the Beta band has the lowest synchrony. 2. Higher correlation between brain regions exists in lower frequency band than that of higher frequency band. 3. The mutual dependency between brain regions and flow of information from one brain area to another brain area increase with higher frequency.
		Findings w.r.t. Emotional States	1. The inverse correlation between various brain regions is stronger during negative emotion than it is during happy emotion, and similarly for active and passive emotion. 2. In negative mental state the brain regions operates more synchronously than in positive emotion, and similarly for passive and active emotion. 3. When experiencing negative emotion as opposed to positive emotion, there is greater interregional information sharing between brain areas, and similarly for active and passive emotion. 4. The amount of directional flow of information is lower in negative emotion than that of positive emotion, and similarly for active and passive emotion. 5. There are only slight variations in the brain network connections of the same emotion in different time periods.
		Findings w.r.t. Brain Regions	1. Electrodes located in same lobe show strong connectivity than the electrodes located in different lobe. 2. Emotions are mainly related to the parietal, central and frontal regions; among which, the parietal region is more responsible for emotion alteration.

HV: High Valence, LV: Low Valence, HA: High Arousal, LA: Low Arousal, PFC: Prefrontal Cortex

VI. CONCLUSION

In this study, the brain area connectivity for different emotions has been illustrated with four features under three sub-frequency bands to investigate how correlation, synchronization, dependence, and information transfer between brain areas change with the changes in emotions. The connectivity feature maps (CFMs) have been constructed with four diverse methods (i.e., PCC, PLV, MI, and TE), and rigorous analysis has been performed, which exposed different remarks to understand brain network connectivity stimulation for emotions, specifically the frequency band: emotions are easily distinguishable in the Gamma frequency band; the strong connectivity is observed in the same brain lobe than different lobes; the parietal region is more responsible for emotion alteration. It is observed that during negative mental state, higher inverse correlation exists between different brain regions than that of positive emotion, and similarly for active and passive emotion. The brain regions operate more synchronously in a negative mental state than a positive one, similarly for passive and active emotion. The higher amount of shared information between brain regions is seen during negative emotion as opposed to positive emotion. The amount of directed flow of information is lower during negative emotion than during positive emotion, and it is similar for active and passive emotion.

Further, the scope remains to investigate brain network connectivity stimulation for emotion through CFMs from EEG. In this study, CFMs are constructed using the most popular DEAP EEG dataset, and the Beta band has the lowest PLV, i.e., the lowest synchrony. According to PLV value, Gamma > Alpha > Beta. This information is consistent with other studies with the DEAP dataset [24]. On the contrary, the study [23] on the SEED [31] dataset found that the overall synchronization (i.e., PLV) of the brain network in lower frequency bands (e.g., Alpha) is greater than the overall synchronization of the brain network in the higher frequency band (e.g., Gamma); although Alpha > Gamma > Beta on PLV value. Therefore, inclusive analyses might be interesting to find out the aspects of different datasets on brain network stimulation.

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