International Journal of Computer Vision and Signal Processing, 14(1), 61-67(2024) ORIGINAL ARTICLE

Investigation of Emotional Effects on Brain Network Stimulation through EEG Signals

Mahfuza Akter Maria, M. A. H. Akhand*

Department of Computer Science and Engineering, Khulna University of Engineering & Technology, Khulna, Bangladesh

Md Abdus Samad Kamal*

Graduate School of Science and Technology, Gunma University, Kiryu, Japan

Abstract

There has been growing evidence in recent years which supports that different brain areas are involved in processing emotions. As a result, research on emotion from the perspective of brain networks is becoming popular. The connectivity strength of this network can be changed with different mental states, which can be identified through different frequency bands of the brain signal. In this study, brain functional and effective connectivity networks have been constructed from DEAP emotional EEG data to study how emotion influences patterns of this connectivity. According to the investigation results, more direct correlations are found under positive emotions than negative ones. The brain regions operate more synchronously, and there is less directed flow of information between brain regions during negative emotions. The correlation between brain regions, whether direct or inverse, is higher in the lower frequency band than in the higher frequency band. The flow of information from one brain region to another brain region increases with higher frequency, and there is more synchrony between brain regions in the Gamma frequency band. The findings of this study have substantial implications for the practical application of EEG-based emotion analysis, as well as prospective avenues for future research in this field.

Contribution of the Paper: Different brain connectivity networks have been investigated for positive and negative emotions under different sub-frequency bands.

Keywords: Electroencephalography, emotion, frequency band, brain connectivity.

IJCVSP

ISSN: 2186-1390
http://cennser.org/IJCVSP

Article History:
Received: 10 August 2023
Revised: 23 September 2023
Accepted: 20 February 2024
Published Online: 25 February 2024

1. Introduction

Neuroimaging techniques are valuable for studying how emotion is processed by the human brain. Emotion research has received increased attention from cognitive scientists and neurobiologists in recent decades, owing to its importance in decision-making and well-being, as well as mood, personality, and psychotic diseases [1]. Electroencephalography (EEG) is a neuroimaging technique that is able to record the electrical impulses produced by neural activity in the brain using its sensors (i.e., electrodes or channels) affixed to the brain; it records the voltage alterations caused by ionic current flows within the brain's neurons [2]. 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 and fast [2], [3]. EEG is a composite signal which is composed of sub-bands such as Alpha (8–12 Hz), Beta (13–29 Hz), and Gamma (30–50 Hz) [4]. The constituent neuronal process activity may be more precisely shown by these sub-bands [5].

Connectivity methods employed on the EEG signal provide valuable information regarding brain connectivity behind emotion. Examples of such methods include Pearson correlation coefficient (PCC) [6], cross-correlation (XCOR) [7], mutual information (MI) [8], normalized MI (NMI) [9], partial mutual information (PMI) [7], and transfer entropy (TE) [4]. Linear functional connectivity such as PCC and

*Corresponding author

Email addresses: maria2007518@stud.kuet.ac.bd (Mahfuza Akter Maria), akhand@cse.kuet.ac.bd (M. A. H. Akhand), maskamal@gunma-u.ac.jp (Md Abdus Samad Kamal)

XCOR can only detect linear dependencies. TE represents effective nonlinear connectivity that measures the directed flow of information between two brain regions, and MI is nonlinear functional connectivity that measures shared information. MI and TE are Information Theoretic measures that are based on Shannon entropy [10]. 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 and investigating brain mechanisms from CFM have become popular recently in the field of emotion research [3, 4, 6, 7, 8, 9, 11, 12, 13, 14, 15, 16, 17]. Wang et al. [9] used NMI as a connectivity method to construct CFM from where it was identified that the range of activated brain regions is broader in the high Arousal low Valence state. Khosrowabadi et al. [15] used magnitude mutual information and squared coherence estimate (MSCE) and MI features, from where it was discovered that various emotional states are accompanied by various types of functional brain connectivity. Liu et al. [16] found the functional network induced by low Valence-Arousal emotion demonstrated more active (higher coherence) functional connectivity than the one induced by high Valence-Arousal emotion. When using the phase slope index (PSI) approach to study brain connectivity, Costa et al. [17] discovered a phenomenon whereby multi-channel EEG signals for sad emotions are more synchronized than those for happy emotions.

Several studies investigated responses of specific brain regions on different mental states by analyzing the CFMs with individual connectivity methods. Gao et al. [3] employed Granger causality (GC) and TE features for classifying stress and calm state; from the GC connectivity matrix, it was found that the parietal and frontal lobes show stronger connectivity during the stress state; and from TE connectivity matrix, discovered that under pressure, there was a greater information exchange between the Fp1 and C4 channels. Chen et al. [6] constructed CFM with PCC and phase locking value (PLV); 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. Kong et al. [11] investigated brain connectivity with the PSI method; and 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. Wang et al. [12] investigated the PLV connectivity matrix and drew a conclusion that emotions are related to mainly the temporal lobe; and during positive and negative emotions, the left and right forebrain produces strong EEG activity, respectively. The study shows that emotions are greatly correlated with the forebrain. Zhu et al. [13] explored phase synchronization of brain signals with phase lag index (PLI) and found that, generally, the connectivity between the channels of the right frontal region was stronger than those of the left frontal region.

The aim of this study is to analyze and understand brain network connectivity stimulation for emotion as positive and negative through CFM from EEG, overcoming the limitations of the existing studies. The existing studies considered a smaller number of method(s) to investigate the brain mechanism behind emotion. There are only a few studies that consider sub-frequency bands to analyze brain responses during emotions. The major contributions of this study are summarized below:

- Diverse connectivity methods are considered for CFM construction and analysis. Three widely used connectivity methods named PCC, PLV, and TE were chosen.
- This study investigates connectivity represented in three sub-frequency bands named Alpha, Beta, and Gamma.

The rest of this study is structured as follows: The methodology to investigate brain mechanisms from CFM is described in Section 2. Section 3 presents the findings from the CFM. At last, section 4 concludes the paper with a few remarks.

2. Methodology

In this study, connectivity is measured using different popular methods on the benchmark EEG dataset. The following subsections describe the EEG dataset and the connectivity methods to construct CFM.

2.1. Dataset Selection and Data Preprocessing

This study utilizes one of the biggest EEG datasets for emotion detection, the Database for Emotion Analysis Using Physiological Signals (DEAP) [18]. In this dataset, 40 emotive music videos were utilized as the stimuli, and the EEG and peripheral physiological signals of 32 individuals (i.e., subjects) are included. The database also includes subjective scores that describe the levels of Valence, Arousal, Liking, and Dominance of the emotional states produced by watching the films. Preprocessed EEG signals from the database were used in this work, where the signal frequency range is 4.0 to 45.0 Hz. There were a total of 40 channels, 32 of which were for EEG signals and the rest 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, the original signal is 63 seconds in length. The first 3 seconds of data are the pre-trial baseline

	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
Channel 1	C(1,1)	C(1,2)	C(1,3)	C(1,4)	C(1,5)
Channel 2	C(2,1)	C(2,2)	C(2,3)	C(2,4)	C(2,5)
Channel 3	C(3,1)	C(3,2)	C(3,3)	C(3,4)	C(3,5)
Channel 4	C(4,1)	C(4,2)	C(4,3)	C(4,4)	C(4,5)
Channel 5	C(5,1)	C(5,2)	C(5,3)	C(5,4)	C(5,5)

(a) CFM for PCC or PLV.

	Channel 1	Channel 2	Channel 3	Channel 4	Channel 5
Channel 1	C(1→1)	C(1→2)	C(1→3)	C(1→4)	C(1→5)
Channel 2	C(2→1)	C(2→2)	C(2→3)	C(2→4)	C(2→5)
Channel 3	C(3→1)	C(3→2)	C(3→3)	C(3→4)	C(3→5)
Channel 4	C(4→1)	C(4→2)	C(4→3)	C(4→4)	C(4→5)
Channel 5	C(5→1)	C(5→2)	C(5→3)	C(5→4)	C(5→5)

(b) CFM for TE.

Figure 1: Connectivity feature map (CFM) creation with different connectivity methods.

which is removed, and the last 60 seconds of data are processed for this study. The brain network's connection mode is difficult to maintain relatively steady between the start and end of data collection (i.e., it does not satisfy the basic assumption of static connection) [16]. So, the time series of 60 seconds is segmented before calculating the connectivity. Candra et al. demonstrated that a segmentation time window of 3-12 seconds preserves the key information of Valence [19]. EEG data are segmented for this study using an 8-second sliding time window with a 4-second overlap. Thus, there are 14 segments totaling 60 seconds. The total number of segments for each participant is 14 × 40 (video) × 32 (channel). EEGLAB [20] is used to filter the signal to extract Alpha, Beta, and Gamma sub-bands. Among the four quality levels available in the dataset, Valence is chosen in this study as it is a well-studied scale to classify emotions into positive and negative. In the dataset, the ratings for Valence range from 1 (low) to 9 (high). Similar to the study [21], Valence is considered as high (HV) for values above 4.5 and low (LV) for less than or equal to 4.5. HV indicates positive emotions, and LV indicates negative emotions.

2.2. Connectivity Method and CFM Construction

Feature extraction is converting inputs to new dimensions, which can be diverse combinations of inputs. This work takes into account several connectivity measures (linear, non-linear, 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. Three candidate popular connectivity methods were chosen from linear functional, non-linear functional connectivity, and non-linear effective connectivity categories. The selected methods are PCC, PLV, and TE.

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

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

here, 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-

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

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

$$TE_{Y\rightarrow X} = H(X_t, Y_t) - H(X_{t+h}, X_t, Y_t) + H(X_{t+h}, Y_t) - H(X_t), \tag{3}$$

Here, H represents Shannon entropy [10]. The fixed bin histogram technique was utilized to calculate the probability which is needed to measure entropy. The number of bins used in the calculation is 10. If future of X, i.e., $X_{(t+h)}$ is denoted by w then Transfer Entropy $TE_{(Y\rightarrow X)}$ can be computed as:

$$TE(w,X,Y) = H(w,X,) + H(X,Y) - H(X) - H(w,X,Y) \tag{4}$$

The ranges of TE value are $TE_{(Y\rightarrow X)} < \infty$. If $TE = 0$, 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. Thus, if there are N electrodes, then the number of acquired features is $N(N-1)/2$ for undirected methods (i.e., PCC, PLV) and $N(N-1)$ for directed connectivity (i.e., TE). The connectivity features extracted from all electrode pairs can be mapped into a matrix (i.e., CFM), as seen in Fig. 1 (for 5-channel EEG). The matrix element at (X, Y) describes the connectivity strength between the signals collected from the Xth and Yth electrodes. The CFM is comparable to a graph's adjacency matrix, where the EEG electrodes and the features are regarded as nodes and edge weights, respectively. 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.

3. Investigation of CFM for Emotion

CFM investigation for brain networks is the main contribution of this study to observe the connectivity depiction of emotion. The response of the brain of a person to an emotion may be more or less different from another person. Therefore, the constructed CFMs with each connectivity method under each frequency band are averaged, and analysis is performed on the CFM with average results for general observation. The analysis is performed in the following subsections in two different modes.

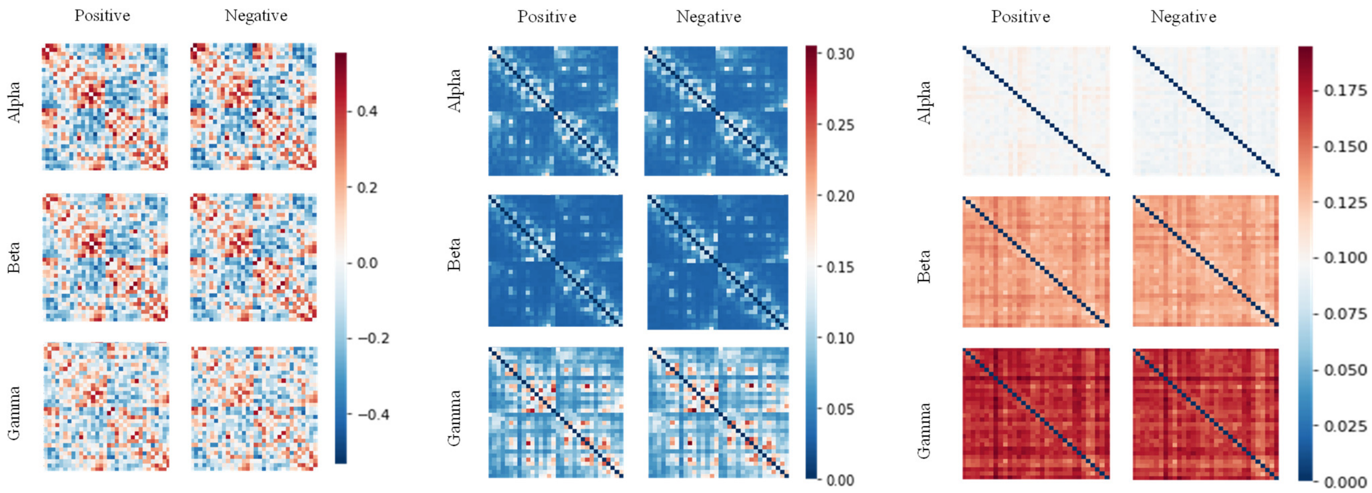
3.1. Effect of Sub-bands on Emotion Analysis

The CFMs created from the three frequency bands Alpha, Beta, and Gamma with the three connectivity methods PCC, PLV, and TE for positive and negative emotions are displayed in Fig. 2. It can be observed for PCC in Fig. 2(a) that 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. It means the correlation between brain regions, either it is a direct correlation or inverse correlation, is higher in the lower frequency band than in that of the higher frequency band. As demonstrated in Fig. 2(b), 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 TE shown in Fig. 2(c), it can be observed that the flow of information from one brain region to another brain region increases with higher frequency. Among the three frequency bands, the positive and the negative CFMs are more easily distinguishable in the Gamma frequency band. A number of existing studies also identified that the Gamma band exposes better observation than the Alpha and Beta bands [14], [22]. So further discussions in the next sections are presented with CFMs from the Gamma band only.

3.2. Connectivity Strength with Emotion Types

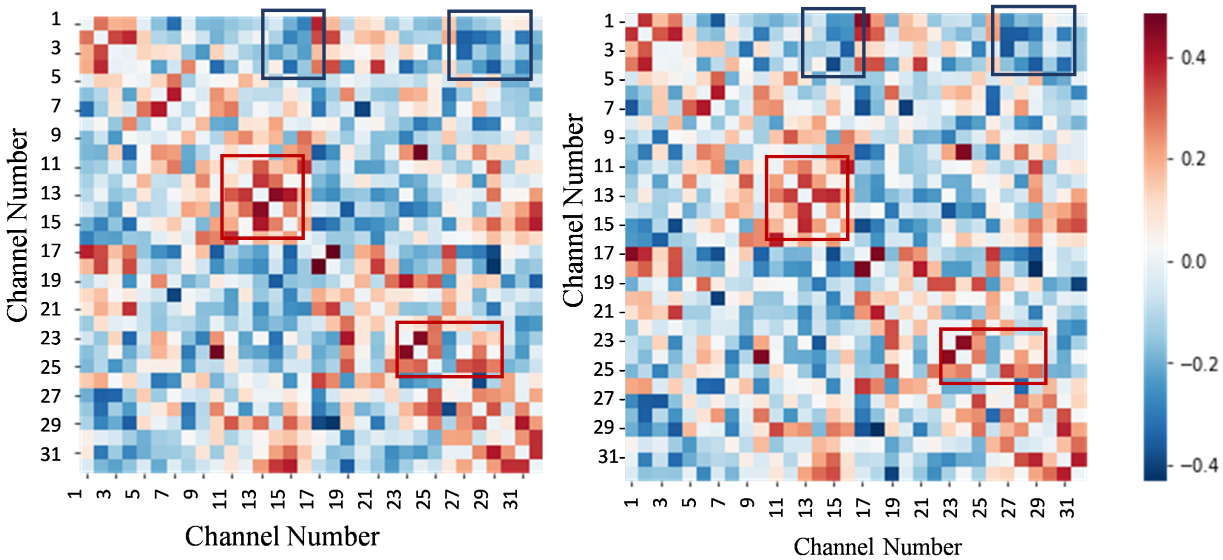
Connectivity methods provide valuable information about brain connectivity behind emotions. Figs. 3-5 show how correlation, phase synchronization, and causal relationship between two brain regions change with emotional changes. How the correlation between two brain regions changes with the changes in emotion can be investigated with CFM constructed from PCC. Fig. 3 shows the CFM constructed using PCC in the Gamma frequency band for positive and negative emotions. The blue regions (negative PCC) represent a linear inverse correlation between two brain regions, and the red regions (positive PCC) represent a direct linear correlation. From Fig. 3, it can be observed that the number of regions having a strongly inverse correlation is higher in negative emotions than that of positive emotions. In Fig. 3, blue-colored regions are darker in CFM of negative emotions than in CFM of positive emotions. For better visualization, such few areas are marked with blue rectangles. It means that brain regions are more inversely correlated during negative emotions. The red regions are darker in positive CFM than that in negative CFM; this means during positive emotions more direct linear correlation exists between brain regions than that in negative emotions. Such few areas are marked with red rectangles. PCC can capture this information, and using this information, brain activity and emotions can be categorized. This information is consistent with the existing studies [6, 23]. The CFM constructed using PCC depicted in the study [6, 23] clearly revealed that, in most cases, inversely correlated regions are more inversely correlated in negative emotions than positive emotions.

PLV describes the phase synchronization between two brain regions. Fig. 4 shows the CFM constructed for positive and negative emotions using PLV in the Gamma frequency band. When the PLV value is 0, the two signals are perfectly independent, a PLV value greater than 0 indicates synchronization between two signals, and a PLV value equal to 1 indicates perfect synchronization. The red pixels of CFM represent an area with a large phase-locking value, while the blue pixels represent an area with a small phase-locking value. Fig. 4 shows that the phase-locking value in positive emotions is relatively lower than the phase-locking value in negative emotions. Such few areas are marked with red rectangles. Therefore, in the negative state, the phase synchronization of distinct brain areas is greater. The larger values indicate that the synergy between different brain regions is enhanced during negative emotions, which results in synchronous oscillations. This information is consistent with the study [12], [24]. According to the study's [12], the phase-locking value in the pleasant condition is lower than in the sad state, indicating that the pleasant mood is less active in the brain area. The author of the study [24] found on the SEED dataset [25] that sadness (which is a negative emotion) has the highest synchronization. This could be due to the fact that sadness triggered more memories and associations. It is thus



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

Figure 2: Connectivity feature map (CFM) creation with different connectivity methods.



(a) Positive (b) Negative

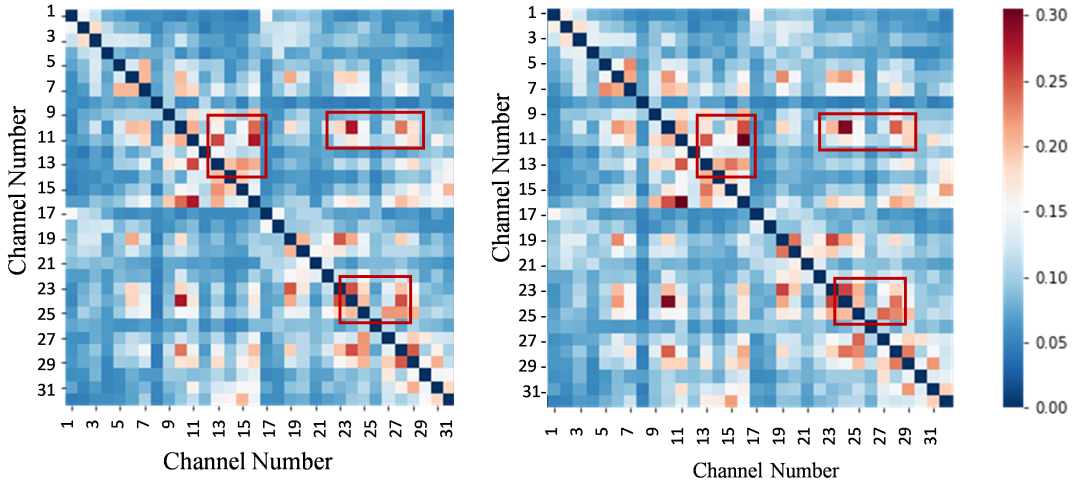
Figure 3: Visualization of CFM Constructed using PCC in Gamma Band for Positive and Negative Emotions.

considered that the human brain pays greater attention to details in negative emotions than in happy emotions.

The CFMs constructed for positive and negative emotions using TE are shown in Fig. 5. The value of TE increases with the increase in the directed flow of information between two brain regions. From Fig. 5, it can be found that the color of Fig. 5(b) is lighter than the color of Fig. 5(a), which can be easily seen through the white rectangular area, indicating the amount of directed flow of information is higher in positive emotions than in negative emotions. All the aforementioned findings of this study are summarised in Table 1 showing outcome through the connectivity strength function CS().

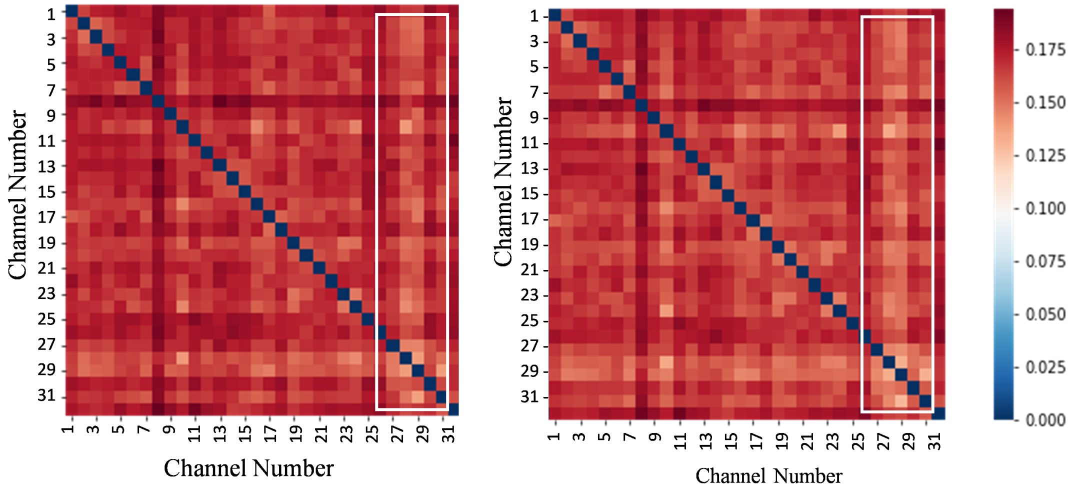
4. Conclusions

In this study, the brain area connectivity has been illustrated for different emotions with three kinds of features under three sub-frequency bands to investigate how correlation, synchronization, and information transfer between different brain regions change with the changes in emotions. The connectivity feature maps (CFMs) have been constructed with three diverse methods (i.e., PCC, PLV, and TE), and rigorous analysis has been performed. It was observed that during negative emotions, the inverse correlation between different brain regions is higher than that of positive emotions. The human brain pays greater attention to details when experiencing a negative emotion than when experiencing a pleasant emotion, and the brain regions operate more synchronously. The amount of directed



(a) Positive (b) Negative

Figure 4: Visualization of CFM Constructed using PLV in Gamma Band for Positive and Negative Emotions.



(a) Positive (b) Negative

Figure 5: Visualization of CFM Constructed using TE in Gamma Band for Positive and Negative Emotions.

flow of information is lower in negative emotions than that of positive emotions. The study also shows remarkable observations on sub-frequency bands' effect and brain region-based correlation on emotion. Among the three sub-bands, the Gamma frequency bands have higher synchrony (i.e., PLV value) when participants watch emotional videos. In contrast, the Beta band has the lowest PLV, i.e., the lowest synchrony. A higher correlation (i.e., PCC value) between brain regions exists in the lower frequency band than in the higher frequency band. The flow of information (i.e., TE value) from one brain region to another brain region increases with higher frequency

References

[1] R. Underwood, E. Tolmeijer, J. Wibroe, E. Peters, L. Mason, Networks underpinning emotion: A systematic review and synthesis of functional and effective connectivity, NeuroImage 243 (2021) 118486.

[2] S. M. Alarcao, M. J. Fonseca, Emotions recognition using EEG signals: A survey, IEEE transactions on affective computing 10 (3) (2017) 374–393.

[3] Y. Gao, X. Wang, T. Potter, J. Zhang, Y. Zhang, Single-trial EEG emotion recognition using granger causality/transfer entropy analysis, Journal of Neuroscience Methods 346 (2020) 108904.

[4] S.-E. Moon, C.-J. Chen, C.-J. Hsieh, J.-L. Wang, J.-S. Lee, Emotional EEG classification using connectivity features and convolutional neural networks, Neural Networks 132 (2020) 96–107.

[5] H. Adeli, S. Ghosh-Dastidar, N. Dadmehr, A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy, IEEE Transactions on Biomedical Engineering 54 (2) (2007) 205–211.

[6] J. Chen, C. Min, C. Wang, Z. Tang, Y. Liu, X. Hu, Electroencephalograph-based emotion recognition using brain connectivity feature and domain adaptive residual convolution model, Frontiers in Neuroscience 16 (2022) 878146.

[7] G. Niso, R. Bruña, E. Pereda, R. Gutiérrez, R. Bajo, F. Maestú, F. Del-Pozo, Hermes: towards an integrated toolbox to charac-

Table 1: Connectivity strength variation with emotions and frequency bands connectivity strength function CS().

Connectivity Method	Emotions	Frequency Bands
PCC Direct Correlation	CS (+Ve Emotion) > CS (−Ve Emotion)	CS (Alpha) > CS (Beta)> CS (Gamma)
PCC Inverse Correlation	CS (+Ve Emotion) < CS (−Ve Emotion)	
PLV Phase Synchronization	CS (+Ve Emotion) < CS (−Ve Emotion)	CS (Gamma) > CS (Alpha)> CS (Beta)
TE Directed Information Flow	CS (+Ve Emotion) > CS (−Ve Emotion)	CS (Gamma)> CS (Beta) > CS (Alpha)

terize functional and effective brain connectivity, Neuroinformatics 11 (2013) 405–434.

[8] S. Farashi, R. Khosrowabadi, EEG based emotion recognition using minimum spanning tree, Physical and Engineering Sciences in Medicine 43 (3) (2020) 985–996.

[9] Z.-M. Wang, S.-Y. Hu, H. Song, Channel selection method for EEG emotion recognition using normalized mutual information, IEEE access 7 (2019) 143303–143311.

[10] C. E. Shannon, A mathematical theory of communication, ACM SIGMOBILE mobile computing and communications review 5 (1) (2001) 3–55.

[11] W. Kong, X. Song, J. Sun, Emotion recognition based on sparse representation of phase synchronization features, Multimedia Tools and Applications 80 (2021) 21203–21217.

[12] Z. Wang, Y. Tong, X. Heng, Phase-locking value based graph convolutional neural networks for emotion recognition, Ieee Access 7 (2019) 93711–93722.

[13] L. Zhu, C. Su, J. Zhang, G. Cui, A. Cichocki, C. Zhou, J. Li, Eeg-based approach for recognizing human social emotion perception, Advanced Engineering Informatics 46 (2020) 101191.

[14] M. A. Maria, M. Akhand, A. A. Hossain, M. A. S. Kamal, K. Yamada, A comparative study on prominent connectivity features for emotion recognition from EEG, IEEE Access 11 (2023) 37809–37831.

[15] R. Khosrowabadi, M. Heijnen, A. Wahab, H. C. Quek, The dynamic emotion recognition system based on functional connectivity of brain regions, in: 2010 IEEE Intelligent Vehicles Symposium, IEEE, 2010, pp. 377–381.

[16] J. Liu, L. Sun, J. Liu, M. Huang, Y. Xu, R. Li, Enhancing emotion recognition using region-specific electroencephalogram data and dynamic functional connectivity, Frontiers in Neuroscience 16 (2022) 884475.

[17] T. Costa, E. Rognoni, D. Galati, EEG phase synchronization during emotional response to positive and negative film stimuli, Neuroscience letters 406 (3) (2006) 159–164.

[18] S. Koelstra, C. Muhl, M. Soleymani, J.-S. Lee, A. Yazdani, T. Ebrahimi, T. Pun, A. Nijholt, I. Patras, Deap: A database for emotion analysis; using physiological signals, IEEE transactions on affective computing 3 (1) (2011) 18–31.

[19] H. Candra, M. Yuwono, R. Chai, A. Handojoseno, I. Elamvazuthi, H. T. Nguyen, S. Su, Investigation of window size in classification of eeg-emotion signal with wavelet entropy and support vector machine, in: 2015 37th Annual international conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2015, pp. 7250–7253.

[20] A. Delorme, S. Makeig, EEGLAB: an open source toolbox for analysis of single-trial eeg dynamics including independent component analysis, Journal of neuroscience methods 134 (1) (2004) 9–21.

[21] M. R. Islam, M. M. Islam, M. M. Rahman, C. Mondal, S. K. Singha, M. Ahmad, A. Awal, M. S. Islam, M. A. Moni, Eeg channel correlation based model for emotion recognition, Computers in Biology and Medicine 136 (2021) 104757.

[22] J. Bi, F. Wang, X. Yan, J. Ping, Y. Wen, Multi-domain fusion deep graph convolution neural network for eeg emotion recognition, Neural Computing and Applications 34 (24) (2022) 22241–22255.

[23] L. Jin, E. Y. Kim, Interpretable cross-subject eeg-based emotion recognition using channel-wise features, Sensors 20 (23) (2020) 6719.

[24] D. Li, Z. Yang, F. Hou, Q. Kang, S. Liu, Y. Song, Q. Gao, E. Dong, Eeg-based emotion recognition with haptic vibration by a feature fusion method, IEEE Transactions on Instrumentation and Measurement 71 (2022) 1–11.

[25] W.-L. Zheng, B.-L. Lu, Investigating critical frequency bands and channels for eeg-based emotion recognition with deep neural networks, IEEE Transactions on autonomous mental development 7 (3) (2015) 162–175.