Sourabh Banik*, Himanshu Kumar, Nagarajan Ganapathy, and Ramakrishnan Swaminathan

Assessment of EEG-PPG Cross Frequency Coherence under Evoked Emotional Arousal

https://doi.org/10.1515/cdbme-2024-2012

Abstract: Emotion influences the daily activity of human life. The complex interaction between the central nervous system (CNS) and peripheral nervous system (PNS) contributes to emotional experiences. Various studies have investigated this interaction during sleep, meditation, deception, and cognition. However, research focusing exclusively on emotion-related interactions is limited. In this work an attempt has been made to assess the CNS and PNS interaction by analyzing Electroencephalogram (EEG) and Photoplethysmogram (PPG) signals during emotional arousal induced by audio-visual stimuli obtained from the DEAP database . EEG signals are divided into four frequency bands: theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-45 Hz). The envelope of EEG and PPG signals is then computed to determine cross-frequency coherence (CFC). The Wilcoxon Rank-sum test is employed to assess the statistical significance of CFC in low (LA) vs. high-arousal(HA) for various electrodes. Results indicate that CFC can discriminate the LA vs HA. Higher CFC is found in HA compared to LA for the beta and gamma bands, while the opposite trend is observed in the theta and alpha bands. The FP1, FC1, and T7 are found to be statistically significant ($p < 0.05$) in differentiating LA with HA. Therefore, this study offers insights into CNS-PNS interaction during emotional arousal.

Keywords: EEG, PPG, Cross Frequency Coherence, Emotion, Arousal

1 Introduction

Emotion is the psychological state of sentiments provoked by either internal factors, external factors, or a combination of both. It is essential and greatly impacts every spectrum of daily human life [**1**]. Out of the different emotional models, Russell's circumplex model, which is dimension-based, is widely utilized in studies related to affective computing [**2**]. According to this model, emotion can be quantified from the aspect of arousal i.e. how intense the emotional state is.

The nervous system and cardiovascular system work in synergy in various emotional states. It is characterized by an intricate interaction. Biologically, the conversion of physical changes into emotions relies on the interaction between the central nervous system (CNS) and peripheral nervous system (PNS). This remains a topic under further research within psychophysiology. The electroencephalogram (EEG), a bio-signal originating from the central nervous system (CNS), records the brain's electrical activity. The brain controls various functions of the peripheral nervous system (PNS), including those associated with heart rate and respiration. Due to its ease of implementation and affordability [**3**], the photoplethysmogram (PPG), a signal originating from the PNS, can be utilized to study neurocardiologic interactions.

Numerous studies have been carried out concerning the connection between the brain and heart during periods of apnea, normal sleep, and meditation [**4**, **5**, **6**]. Khandoker et al. showed that the coherence between Electrocardiogram (ECG) and EEG signals is higher during normal breathing events in Rapid Eye Movement (REM) sleep than in Non-Rapid Eye Movement (NREM) sleep [**6**]. Even though EEG and cardiovascular signals have uncorrelated amplitudes, coherency can represent the extent of the linear association between these signals [**7**].

The coherency shows how much of one time series' variability can be explained by its linear relationship with the other series at a particular frequency. The concept of coherence has been successfully applied in understanding the interactions between the heart and lungs during postural change [**8**], as well as in studying neurophysiological states like typical sleep patterns [**9**]. In [**6**] it is observed that there is a positive relationship between heart coherence and peak/relative alpha power during meditation, but this coherence is not present during the baseline condition. However, these type of interaction-based studies in the domain of emotion is limited. This study aims to assess how the amplitude envelope of the PPG and various EEG frequency bands interact during high arousal (HA) and low arousal (LA) through cross-frequency coherence.

***Corresponding author: Sourabh Banik,** Indian Institute of Technology Madras, Chennai, India, sourabh99ind@gmail.com
Himanshu Kumar, Indian Institute of Technology Madras, Chennai, India
Nagarajan Ganapathy, Indian Institute of Technology Hyderabad, Hyderabad, India
Ramakrishnan Swaminathan, Indian Institute of Technology Madras, Chennai, India

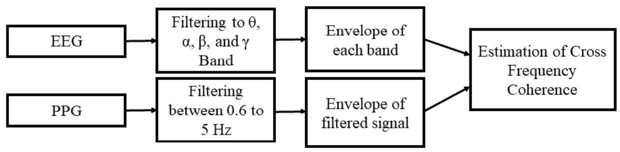

Fig. 1: Block diagram for cross-frequency coherence calculation

2 Methodology

Figure 1 illustrates the computational process block diagram of the cross-frequency coherence-based method employed in this study.

2.1 Database description

EEG and PPG signals from the DEAP database have been used for this investigation. EEG and PPG signals are recorded during the observation of 40 unique one-minute video clips using a Biosemi ActiveTwo system. EEG is being collected using 32 AgCl electrodes, and PPG is being collected through one channel. The dataset includes physiological signals from 32 participants. These signals are acquired at a sampling rate of 512 Hz [**10**].

The data of participants is collected at two distinct sites: the first 22 at Twente and the last 10 at Geneva. The quality of these signals also varies. Particularly, the PPG datasets of the final 10 subjects display significant noise interference, leading to distorted waveforms. This complicates the extraction of crucial information from these signals. Consequently, this paper chooses to utilize data from the initial 22 subjects only [**11**]. Using the arousal ratings, the videos watched by participants are divided into low arousal (LA) and high arousal (HA) categories. Videos rated above 5 are considered high arousal, whereas those rated below 5 are classified as low arousal. Similarly, the corresponding EEG and PPG signals are sorted accordingly.

2.2 Preprocessing

The EEG signals from all 32 channels are decomposed into four bands namely θ(4-7 Hz), α(8-12 Hz), β(13-30 Hz), and γ(30-45 Hz). PPG indicates heart activity indirectly by measuring blood volume changes with each heartbeat. However, it is affected by arterial stiffness, peripheral resistance, and vascular tone. To minimize these effects, the trend is corrected by subtracting temporal low-frequency drift, calculated using a 256-point moving average filter [**10**]. Additionally, a band-pass filter with a cutoff frequency of 0.6 Hz to 5 Hz is applied to extract important information [**12**]. Then the the extracted PPG signals are subjected to z-score normalization.

2.3 Amplitude envelope

The envelope of EEG and PPG is obtained by using Hilbert transform [**7**]. If $x(t)$ is a real-valued signal, its analytic signal $x_a(t)$ is given by the Hilbert transform:

$$x_a(t) = x(t) + j \cdot \mathcal{H}[x(t)] \tag{1}$$

where j is the imaginary unit and $\mathcal{H}[x(t)]$ denotes the Hilbert transform of $x(t)$. $\mathcal{H}[x(t)]$ can be defined as:

$$\mathcal{H}(x(t)) = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{x(\tau)}{t-\tau}\, d\tau \tag{2}$$

Finally, the envelope of the analytic signal is given by:

$$e(t) = |x_a(t)| \tag{3}$$

2.4 Cross-frequency coherence (CFC)

It calculates the magnitude square coherence among the envelope of the filtered PPG signal and different EEG signal bands. To determine this, Welch's method of overlapped averaged periodograms has been employed. It is evaluated as

$$\mathrm{CFC}_k(f) = \frac{|P_{EP}(f)|^2}{P_{\mathrm{EEG}}(f) P_{\mathrm{PPG}}(f)} \tag{4}$$

Here, $P_{\mathrm{EEG}}(f)$ and $P_{\mathrm{PPG}}(f)$ represent the spectral power densities of the EEG and the PPG signal envelope, respectively. $P_{EP}(f)$ denotes the cross-power spectral density between the EEG amplitude and the PPG signal. The magnitude of CFC varies with frequency and has values ranging from 0 to 1, indicating the degree of correspondence between two signals. A coherence value of 1 means the two signals are completely related, while a value of 0 means the signals are completely independent [**13**].

2.5 Statistical analysis

The CFC is calculated for both annotated high and low-arousal EEG-PPG signals. This process is repeated for all the electrodes and all frequency bands. Further, the Wilcoxon rank sum test is performed to assess significance levels of CFC for different arousal levels [**14**].

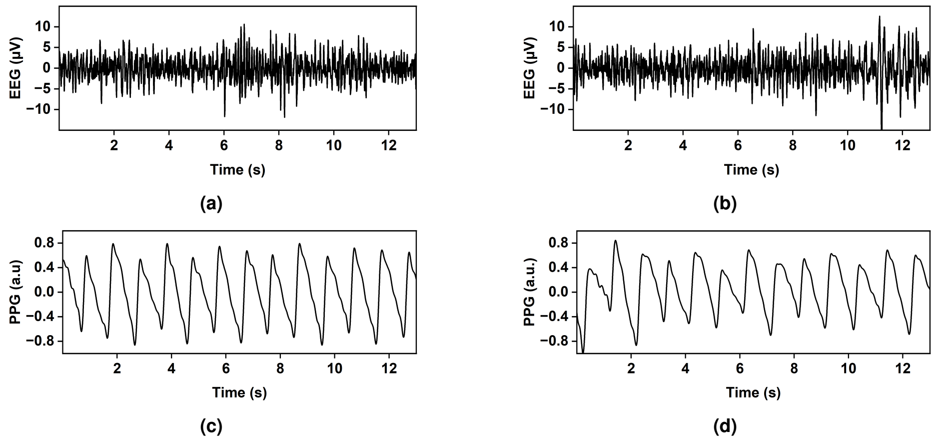

Fig. 2: Representative EEG signal for LA (a), HA (b) for electrode FC1, and PPG signal for LA (c), and HA (d) of a subject

3 Results and Discussion

Tab. 1: Statistically significant electrodes and bands

Electrode	Band			
	Theta	Alpha	Beta	Gamma
FP1	-	-	-	*
FC1	-	-	*	-
T7	-	-	*	-

* (p< 0.05)

Figure 2 illustrates EEG and PPG signals recorded from a participant during low and high-arousal videos. The signals exhibit greater variability during low-arousal videos, yet visual inspection alone does not yield concrete conclusions.

Fig. 3 shows the topographical variation of CFC throughout the brain for both the LA and HA states in the case of theta, alpha, beta, and gamma bands respectively. In the theta band, during LA elicitation, EEG signals of anterior frontal and occipital region are slightly coherent with the PPG signal. Whereas, during high arousal elicitation, an increase of CFC can be seen in frontal, anterior frontal,fronto-central, temporal, and occipital electrodes. For the alpha band, during LA elicitation, the coherence can be seen in the parietal region. During high arousal, coherence is noticeable in the parietal and parieto-occipital regions. In the beta and gamma bands, coherence is greater during low arousal than high arousal, mainly in the frontal, fronto-central, parietal, and occipital regions of the left hemisphere for low arousal. For the gamma band, coherence is primarily seen in the frontal, fronto-central, and centro-parietal regions. In this study, the EEG theta band-PPG interaction in high-arousal videos achieves the highest CFC value of 0.365, while the beta band-PPG interaction obtains the lowest CFC value of 0.1325.

Another interesting fact is that, as the frequency band increases the CFC also decreases till the beta band. But In the case of sleep apnea opposite trend has been seen between

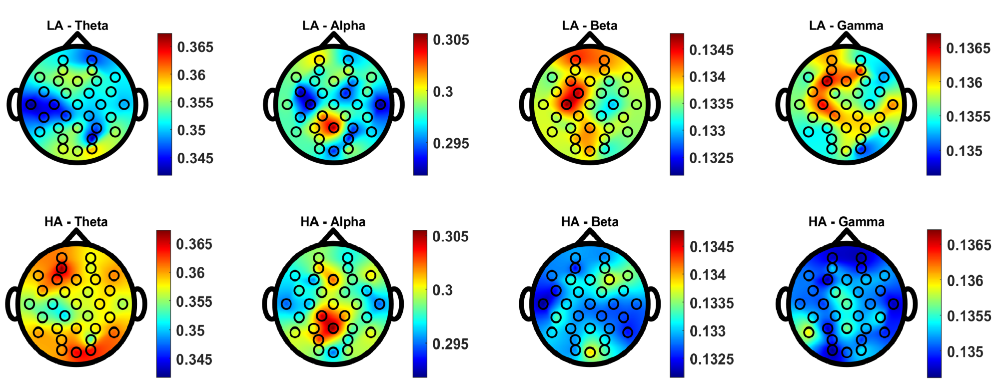

Fig. 3: The topography of CFC for low arousal (upper row) and high arousal (lower row) cases in different frequency bands (from left to right: theta, alpha, beta, and gamma)

EEG and ECG [**15**]. Table 1 shows the statistically significant electrodes in LA and HA from the CFC aspect. It can be seen that CFC in FP1 (gamma band), FC1 (beta band), and T7 (beta band) electrodes are significant electrodes ($p<0.05$) for differentiating HA and LA states. This indicates left hemisphere seems to be pivotal in segregating LA and HA states. Moreover, the significance of the interaction between left hemisphere-based frontal EEG and cranial PPG in eliciting emotion has been emphasized in [**16**].

4 Conclusion

This study aims to understand how the brain and heart interact by analyzing the relationship between EEG and PPG signals during emotional elicitation by audio-visual stimuli. Using data from the DEAP database, the study finds that as arousal levels rise, CFC between EEG and PPG signals generally decreases in the beta and gamma bands. However, CFC increases in the theta and alpha bands for increasing arousal levels. The fronto-centro-temporal region seems crucial for distinguishing between LA and HA stimuli from the aspect of the CFC. Enhanced understanding of EEG-PPG dynamics in response to arousal-inducing stimuli can contribute to better comprehension of disorders related to emotions.

Author Statement

Research funding: The author state no funding involved. Conflict of interest: Authors state no conflict of interest.

References

[1] Scherer, Klaus R. Psychological models of emotion. In: The neuropsychology of emotion. New york: Oxford University Press; 2000.

[2] Himanshu K, Nagarajan G, Subha D P, Ramakrishnan S. EEG based emotion recognition using entropy features and Bayesian optimized random forest. Current Directions in Biomedical Engineering 2021; 7(2):767-770

[3] Banik S, Kumar H, Ganapathy N, Swaminathan R. Exploring Central-Peripheral Nervous System Interaction Through Multimodal Biosignals: A Systematic Review. IEEE Access 2024; 12:60347-60368.

[4] Khandoker AH, Karmakar CK, Palaniswami M. Interaction between sleep EEG and ECG signals during and after obstructive sleep apnea events with or without arousals. Computers in Cardiology 2008; 685-688.

[5] Abdullah H, Maddage N, Cosic I, Cvetkovic D. Brain and heart interaction during sleep in the healthy and sleep apnoea. In: IEEE EMBS Conference on Biomedical Engineering and Sciences (IECBES). Buenos Aires: IEEE; 2010.

[6] Kim DK, Lee KM, Kim J, Whang MC, Kang SW. Dynamic correlations between heart and brain rhythm during Autogenic meditation. Frontiers in human neuroscience 2013;7:414.

[7] Clerico A, Tiwari A, Gupta R, Jayaraman S, Falk TH. Electroencephalography amplitude modulation analysis for automated affective tagging of music video clips. Frontiers in computational neuroscience 2018; 11:115.

[8] Mary H, Singh D, Deepak KK. Assessment of interaction between cardio-respiratory signals using directed coherence on healthy subjects during postural change. IRBM 2019; 40(3):167-173

[9] Jurysta F, Van De Borne P, Migeotte PF, Dumont M, Lanquart JP, Degaute JP, et al. A study of the dynamic interactions between sleep EEG and heart rate variability in healthy young men. Clinical neurophysiology 2003;114(11):2146-55.

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

[11] Tong Z, Chen X, He Z, Tong K, Fang Z, Wang X. Emotion recognition based on photoplethysmogram and electroencephalogram. In: IEEE 42nd annual computer software and applications conference (COMPSAC). Tokyo: IEEE; 2018.

[12] Merino-Monge M, Castro-García JA, Lebrato-Vázquez C, Gómez-González IM, Molina-Cantero AJ. Heartbeat detector from ECG and PPG signals based on wavelet transform and upper envelopes. Physical and Engineering Sciences in Medicine 2023; 46(2):597-608

[13] Daly I, Malik A, Hwang F, Roesch E, Weaver J, Kirke A, et al. Neural correlates of emotional responses to music: an EEG study. Neuroscience letters 2014;573:52-57.

[14] Nguyen T, Khosravi A, Creighton D, Nahavandi S. EEG data classification using wavelet features selected by Wilcoxon statistics. Neural Computing and Applications 2015; 26:1193-1202

[15] Polepogu Rajesh, Vaegae Naveen Kumar. Rhythms-Based Coherence Analysis Between Brain and Heart of Sleep Disorder Samples using MSC. International Journal of Engineering Trends and Technology 2022; 70(6):287-299.

[16] Shriram R, Daimiwal N. Statistical Analysis of Coherence Between Electrical and Hemodynamic Brain Signal. InSmart Sensors Measurements and Instrumentation: Select Proceedings of CISCON 2021; 211-219