

A Network Physiology Approach to Brain-Heart Interaction for Affective State Characterization Using Photoplethysmography Features

Feryal A Alskafi¹, Ahsan H Khandoker¹, Faezeh Marzbanrad², Herbert F Jelinek¹

¹ Khalifa University, Abu Dhabi, United Arab Emirates

² Monash University, Melbourne, Australia

Abstract

Emerging evidence highlights bidirectional, complex, and nonlinear communication between heart and brain dynamics. While several studies have applied artificial intelligence to distinguish and classify emotions based on static EEG and PPG features, little research has focused on the network elements of these interactions across different emotional states. Using data from the DEAP dataset, which includes EEG and PPG signals recorded while participants viewed emotionally evocative music videos, this study applied a novel network analytic approach to examine dynamic interactions between brain rhythms and PPG features (amplitude, peak-to-peak interval, and pulse width amplitude). Time-delay stability of partial cross-correlation was used to identify emotional states. Significant correlations emerged between EEG rhythms and both PWA and PPI across affective states ($p < 0.05$). However, reverse relationships, where PPI or PWA influenced EEG bands, were not significant. Furthermore, the correlation between PPG amplitude and EEG rhythms, or vice versa, did not significantly differentiate between affective states, suggesting that PPG amplitude is less indicative of emotional states than PPI or PWA. The findings establish EEG-PWA and EEG-PPI connectivity as reliable indicators of affective states and provide insights for developing explainable graph-based emotion recognition systems.

1. Introduction

Physiological-based emotion recognition has recently gained prominence in emotional healthcare, human-computer interaction, and multimedia content recommendation research. Numerous studies have shown the effectiveness of artificial intelligence in detecting and classifying emotions through physiological responses. However, comprehensive research on the network dynamics underlying these interactions across different emotional states is still lacking. Traditionally, emotion recognition using

physiological signals has relied on static features for classification. However, physiological systems continuously interact and coordinate their dynamics. New tools and approaches in network physiology have emerged to examine brain-organ interactions and their connections with various emotional states. Research suggests that analyzing network maps of physiological communication can uncover new biomarkers for illness diagnosis and progression [1].

Emotions can be characterized by physiological changes in both the central nervous system (CNS) and the autonomic nervous system (ANS), which regulate peripheral physiological responses. Electroencephalography (EEG) is widely used to assess CNS responses linked to emotions [2], while photoplethysmography (PPG) is a cost-effective, non-invasive technique to assess ANS function by detecting variations in blood volume under the skin [3]. Analyzing PPG and EEG signals requires consideration of their different output dynamics, non-stationary nature, and constant fluctuations. These interactions occur on multiple temporal scales and often exhibit synchronized bursting activity with specific time delays. To address this complexity, the present study used a framework proposed by Marzbanrad et al. [4], building on the time delay stability framework introduced by Bashan et al. [1]. This framework differentiates between primary and non-primary links in a complex network by isolating directional connections between each system pair while controlling for the influence of other nodes. It determines a stable delay that optimizes the partial cross-correlation between each pair of nodes while accounting for other network components [4,5].

2. Methodology

2.1. Data

The Database for Emotion Analysis using Physiological Signals (DEAP) is a publicly available dataset containing recordings of EEG and peripheral physiological signals from 32 participants [6]. Data was collected as participants

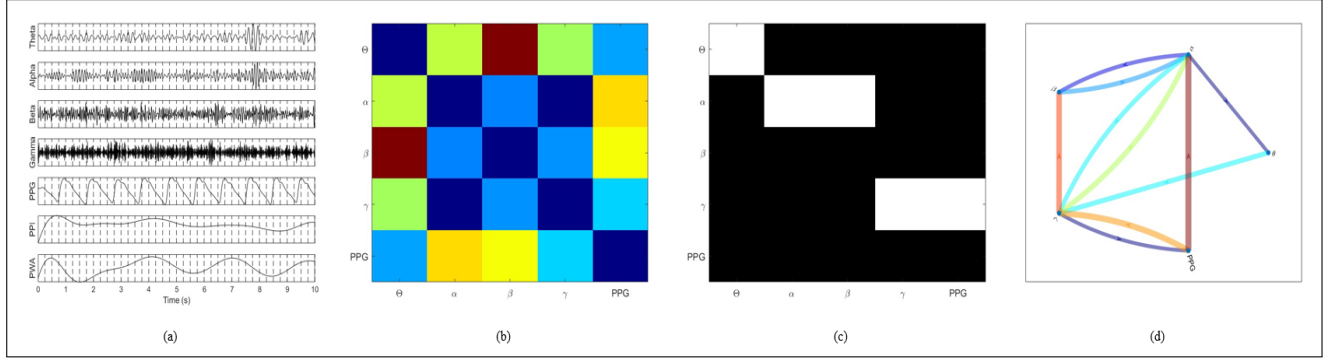


Figure 1: The proposed network analysis method is based on the following steps: (a) Pre-processing input signals. (b) Computing the N^{th} -order partial cross-correlations for all time windows. (c) Visualizing time delay stability within each window; white regions denote a consistent delay, while black indicates instability. Persistent stability across multiple segments indicates overall coupling stability. (d) Evaluating all windows to ascertain the percentage of time exhibiting stable time delays for each link, reflecting its strength. Coupling strength is quantified as the percentage of time with stable time delays.

watched a series of 40 one-minute music videos designed to elicit various emotional responses. This study included arousal and valence responses, which were categorized on a scale of 1 to 9 as high (H), low (L), arousal (A), or valence (V). Recorded signals were down-sampled to 128 Hz. The trend of EEG signals was removed by subtracting the temporal low frequency drift, artifacts from eye and muscle movements were eliminated, and a band-pass frequency filter was applied from 4 Hz to 45 Hz. This study examined eight EEG channels representing the frontal, temporal, and occipital lobes (Fp1, Fp2, C3, C4, O1, O2, T7, and T8). Each EEG channel recorded four distinct brain rhythms (Figure. 1a): theta (4–7 Hz), alpha (8–12 Hz), beta (13–29 Hz), and gamma (30–45 Hz). To reduce noise interference from PPG signals, a 4th-order Chebyshev II filter was utilized [7]. The pulse signal's peak and trough indicate the systole and diastole phases of the cardiac cycle, respectively. The vertical distance between the diastoles and preceding systoles was assessed as pulse wave amplitude (PWA). The pulse-pulse interval (PPI) was defined as the time difference between two consecutive systole points [8].

2.2. Network Analysis

To assess the link strength between each pair of rhythms in the network, x and y , while mitigating the influence of n additional systems $z_1, z_2, \dots, z_N$, the n^{th} order partial cross-correlation was applied recursively as follows:

$$\rho_{xy|z_1, z_2, \dots, z_n}(\tau) = \frac{\rho_{xy|z_1, z_2, \dots, z_n}(\tau) - \rho_{xz_n|z_1, z_2, \dots, z_{n-1}} \cdot \rho_{yz_n|z_1, z_2, \dots, z_{n-1}}(\tau)}{\sqrt{1 - \rho_{xz_n|z_1, z_2, \dots, z_{n-1}}^2} \sqrt{1 - \rho_{yz_n|z_1, z_2, \dots, z_{n-1}}^2}(\tau)}$$

The coefficient is determined via a regression approach, with the partial cross-correlation coefficient being between the residuals of x and y after regression on z . The function was calculated for each overlapping normalized segment v of length L , taking into account the time delay τ (Figure. 1b). Then, for each segment v , the delay τ_v^0 that maximizes the function $\rho_{xy|z_1, z_2, \dots, z_N}(\tau)$ was identified. The generally constant delay in a given limited range demonstrates stable coupling, and overall stability necessitates at least four out of five successive segments with stable time delays (Figure. 1c). The percentage of time for observed stability indicates the strength of the links (Figure. 1d). The threshold level was determined through surrogate analysis to be 0.4 [4]. Prior to quantifying the group average strength of a particular network link, outliers in network link strength assessment resulting from artifacts and individual differences were removed by calculating the distribution and standard deviation of time-delay stability percentages derived from all subjects within the group. Subjects whose values for a given link exceeded the group average plus two standard deviations were excluded from the analysis. The remaining subject data in the group was then used to compute an average for the link, thereby eliminating outliers from the calculation of group-averaged link strength. This procedure was iteratively performed for each link in the network, ensuring comprehensive treatment of potential outliers [9].

3. Results

Graph networks were used to visualize significant brain-heart interactions (BHI) related to PPG amplitude (Figure. 2a), PPI (Figure. 2b), and PWA (Figure. 2c). The

study aimed to assess how well these bi-directional links could distinguish between four affective states. Using the Kruskal-Wallis test at a significance level of $\alpha_{threshold} = 0.05$, no significant differences were found in interactions between PPG amplitude and the four brain rhythms across affective states. However, significant differences were observed in the interactions between EEG rhythms and both PWA and PPI. Pairwise Wilcoxon signed-rank tests, with Bonferroni correction ($\alpha_{adjusted} = 0.0083$), were then used to identify which affective states differed.

Significant differences in PPI interactions were observed between specific affective state pairs. Notably, $\theta \rightarrow$ PPI, $\beta \rightarrow$ PPI, and $\gamma \rightarrow$ PPI interactions differed significantly between HALV and LAHV ($P - values < 0.0022$). Additionally, $\theta \rightarrow$ PPI and $\alpha \rightarrow$ PPI showed significant differences between LAHV and LALV ($P - values < 0.0078$). PWA interactions exhibited even more pronounced differences. For instance, $\beta \rightarrow$ PWA and $\theta \rightarrow$ PWA differed significantly between HAHV and HALV ($P - values < 0.0066$). Furthermore, $\theta \rightarrow$ PWA, $\beta \rightarrow$ PWA, and $\gamma \rightarrow$ PWA were significantly different between HAHV and LAHV, as well as between HALV and LAHV ($P - values < 0.0074$). Finally, $\alpha \rightarrow$ PWA, $\beta \rightarrow$ PWA, and $\gamma \rightarrow$ PWA interactions differed significantly between LAHV and LALV ($P - values < 0.0054$).

The results indicate that while PPG amplitude interactions with brain rhythms did not show significant differences across affective states, both PPI and PWA interactions did, with notable distinctions between specific state pairs. The significant PPI findings, reflecting the time interval between consecutive heartbeats, highlight its sensitivity to emotional valence and arousal, underscoring the role of these BHIs in autonomic regulation during different emotional contexts [10]. The pronounced differences in PWA interactions suggest that it may be a more sensitive measure for detecting emotional state changes. The consistent significance across various brain rhythm-PWA interactions indicates that blood flow regulation is particularly responsive to emotional states, reinforcing the idea that peripheral vascular changes offer valuable insights into the relationships between emotion, behavior, and physiological responses [11].

4. Conclusion

The differential sensitivity of BHI, particularly involving PPI and PWA, to various affective states suggests that these physiological metrics can serve as reliable indicators of emotional arousal and valence. The significant differences observed in specific interactions highlight the complex, multidimensional nature of affective states and the intricate physiological processes that underlie them. Future research will explore the potential applications of

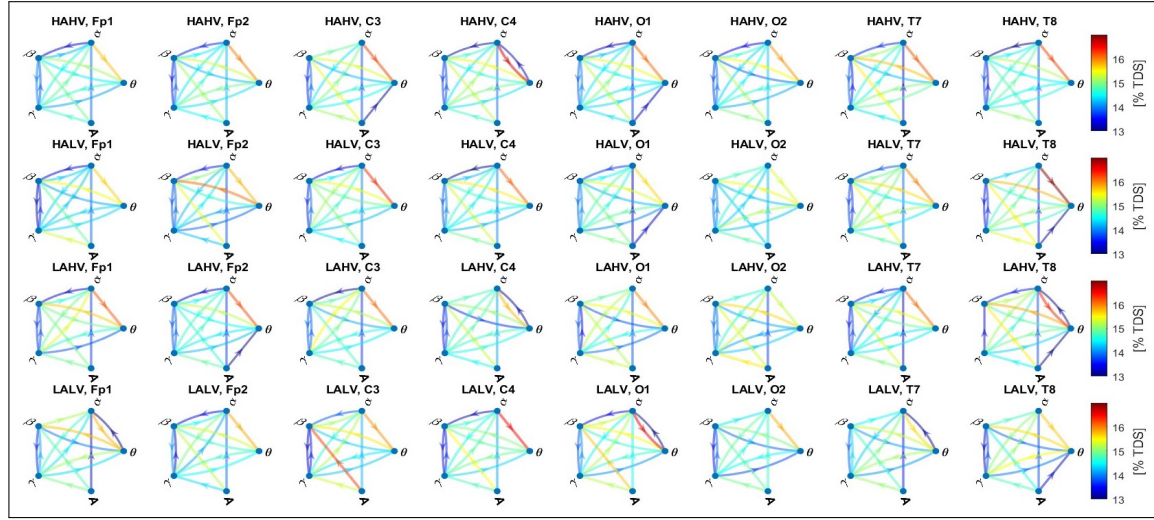
these findings in affective computing and mental health monitoring, as well as expand the analysis to include additional physiological measures.

References

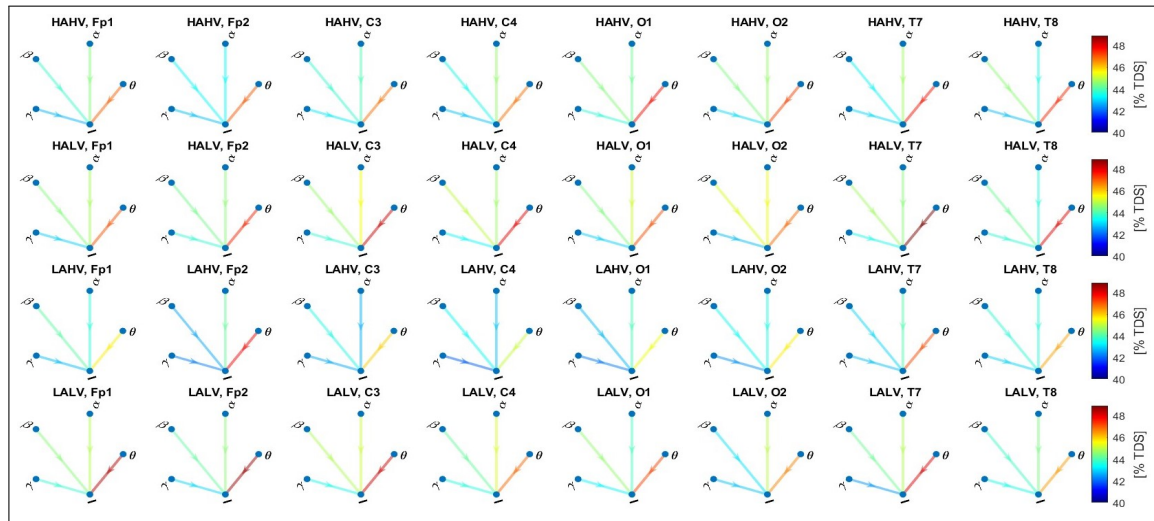
- [1] Bashan A, Bartsch RP, Kantelhardt JW, Havlin S, Ivanov PC. Network physiology reveals relations between network topology and physiological function. *Nature Communications* 2012;3(1):702.
- [2] Liu H, Zhang Y, Li Y, Kong X. Review on emotion recognition based on electroencephalography. *Frontiers in Computational Neuroscience* 2021;15:84.
- [3] Biswas D, Simões-Capela N, Van Hoof C, Van Helleputte N. Heart rate estimation from wrist-worn photoplethysmography: A review. *IEEE Sensors Journal* 2019;19(16):6560–6570.
- [4] Marzbanrad F, Yaghmaie N, Jelinek HF. A framework to quantify controlled directed interactions in network physiology applied to cognitive function assessment. *Scientific Reports* 2020;10(1):18505.
- [5] Alskafi F, Khandoker A, Marzbanrad F, Jelinek H. Brain-heart interactions modulate EEG activity during elicited emotional states. *Computing in Cardiology. IEEE, Institute of Electrical and Electronics Engineers*, 2023; .
- [6] Koelstra S, Muhl C, Soleymani M, Lee JS, Yazdani A, Ebrahimi T, Pun T, Nijholt A, Patras I. DEAP: A database for emotion analysis using physiological signals. *IEEE Transactions on Affective Computing* 2011;3(1):18–31.
- [7] Liang Y, Elgendi M, Chen Z, Ward R. An optimal filter for short photoplethysmogram signals. *Scientific Data* 2018; 5(1):1–12.
- [8] Khandoker AH, Luthra V, Abouallaban Y, Saha S, Ahmed KI, Mostafa R, Chowdhury N, Jelinek HF. Suicidal ideation is associated with altered variability of fingertip photoplethysmogram signal in depressed patients. *Frontiers in Physiology* 2017;8:501.
- [9] Ivanov PC, Wang JW, Zhang X, Chen B. The new frontier of network physiology: Emerging physiologic states in health and disease from integrated organ network interactions. *2019 20 MATRIX Annals* 2021;237–254.
- [10] Rodrigues MCJ, Postolache O, Cercas F. The influence of stress noise and music stimulation on the autonomous nervous system. *IEEE Transactions on Instrumentation and Measurement* 2023;72:1–19.
- [11] Cook MR. Psychophysiology of peripheral vascular changes. In *Cardiovascular Psychophysiology*. Routledge, 2017; 61–84.

Address for correspondence:

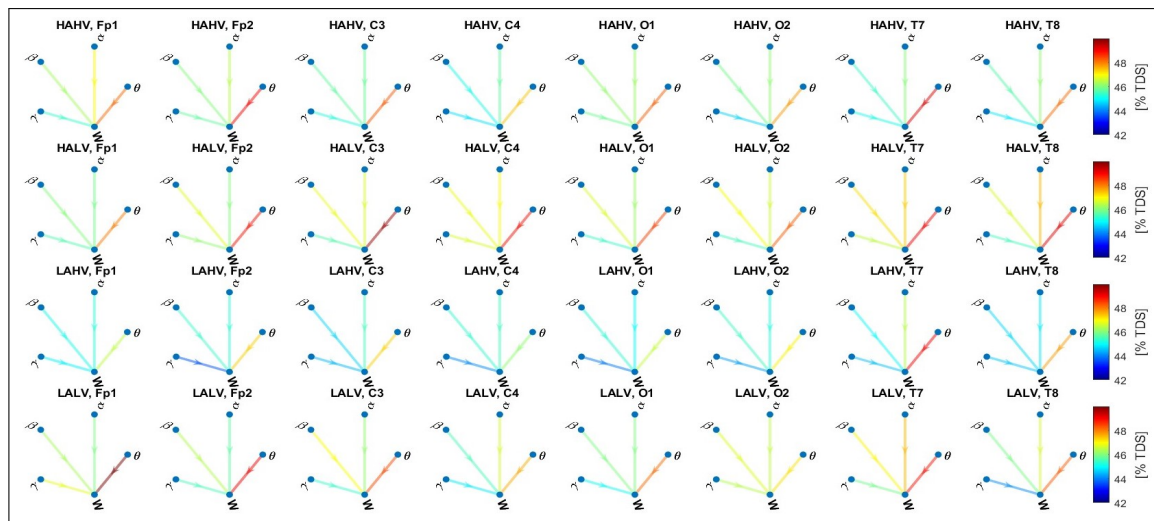
Feryal A. Alskafi
Department of Biomedical Engineering, Khalifa University, Abu Dhabi, UAE
100057997@ku.ac.ae



(a)



(b)



(c)

Figure 2: Group-averaged networks illustrating above threshold interactions between (a) PPG amplitude [A] (Threshold = 13%), (b) PPI [I] (Threshold = 40%), and (c) PWA [W] (Threshold = 41%) with brain rhythms (θ , α , β , γ) across eight cortical regions and affective states. Color coding reflects the percentage of stable time delay indicating coupling strength.