HRV Connectivity Metrics as Indicators of Interpersonal Agreement in Dialogue

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Abstract

*Heart rate (**HR**) is known to be influenced by the emotional state of the subject and is commonly used as a proxy indicator of stress. The most common way humans interact is through conversation, which can be labeled as sympathetic when both participants agree on ideas, and antipathetic when they are in disagreement.*

*A group of 38 participants were invited to engage in conversation with a colleague while their ECG signals were synchronously recorded using a g.USBamp system, with separate grounds and reference electrodes for each participant. Subjects were randomly assigned to either a sympathetic or antipathetic conversation, based on a preliminary interview with a moderator to balance both types. Each conversation lasted approximately twenty minutes, from which both **HRV** signals were obtained via standard interpolation methods and R-peak detection. Four connectivity metrics were estimated from each **HRV** pair: Weighted Phase Lag Index (WPLI), Phase Locking Value (PLV), Coherence (Coh), and Phase Lag Index (PLI). Statistical comparisons were conducted for each metric, showing significance in the expected direction for WPLI and Coherence ($p < 0.05$). Due to the limited sample size, a permutation analysis with 10,000 iterations was performed, yielding significance ($p < 0.05$) for Coherence only.*

*This experiment demonstrates that **HR** is modulated by conversational dynamics and reinforces its use for evaluating human interactions.*

1. Introduction

Sciences based on the study of behavior, such as education or psychology, aim to find better ways to explain human interactions. In recent years, the term *affective computing* has become popular as one of the areas that seeks to translate knowledge of human behavior into computer systems that help evaluate it and, in some cases, make use of this information, which is often considered subjective and lacking reproducibility [1]. That is why objective indices such as physiological signals are used to better understand these processes.

Previous studies such as those by Descorbeth et al. [2] use near-infrared spectroscopy (fNIRS) signals to evaluate brain region activation during dialog tasks between two individuals. In that study, pairs were formed into two groups with high and low socioeconomic disparity. The conversation in that experiment was guided by the experimenter, such that each participant had listening and speaking periods, greatly limiting the exchange of ideas. The results of that experiment indicate that the social context alters the activation regions of the cerebral cortex, primarily during listening. Pérez et al. [3] conducted a study where a group of people were asked to listen to the same story while their cardiac signals were recorded during the session. The subjects in this study participated on different days and had no interaction other than listening to the same story. The analysis carried out in this work consisted of aligning the recordings and evaluating the synchronization of heart rate among all subjects. It was reported that for those who paid attention, a greater synchronization of heart rate was identified. This could be due to the fact that the story itself and the empathy it generated modulate the listeners' heart rate.

Animal studies have further demonstrated that brain structures involved in emotional regulation also influence cardiovascular function. Miller [4] reviewed evidence from hominid models showing that damage or removal of the amygdala results in altered social behavior and changes in heart rate. Human studies have also revealed associations between amygdalar function, emotional expression, and cardiac dynamics [5]. Moreover, recent work has emphasized the bidirectional interactions between cortical activity and autonomic mechanisms underlying homeostatic regulation [6, 7]. These investigations support the notion that cortical processes can modulate autonomic outputs—such as heart rate variability (**HRV**)—and that autonomic signals can, in turn, influence cortical activity.

Given this complex interplay, studying processes that modulate emotional states—such as social interaction—is valuable not only for advancing our understanding of brain–body dynamics but also for fostering interdisciplinary applications in fields such as education and psychology.

2. Methods and Materials

2.1. Data

A total of 38 participants were invited to engage in a conversation with a colleague while their ECG signals were synchronously recorded. All conversations were video-recorded for future analysis. Participants were randomly assigned to either a **sympathy** or **antipathy** interaction, based on a preliminary interview with a moderator to ensure balanced assignment across conditions. Moderator also guarantees that each conversation last at least 20 minutes and no longer than 30. After validating records a total of **eight** conversation were marked as **antipathy** and **eleven** as **sympathy**.

Each participant signed an informed consent form and was free to withdraw from the experiment at any time. The study was approved by the university's ethics committee under Folio 256 and conducted in accordance with the principles of the Declaration of Helsinki. All personal data were anonymized, and participants' identities were protected to ensure data privacy and confidentiality.

ECG signals were acquired using a g.USBamp amplifier system (g.tec, Austria, 2019) at a sampling rate of 512 Hz. A Butterworth band-pass filter with a frequency range of 0.1–100 Hz was applied during acquisition. The amplifier supports up to four independent ground systems; for each participant, three electrodes were placed as follows: the right clavicle (active), the left clavicle (reference), and the left ischium (ground).

2.2. Signal processing

For **HRV** extraction R peaks were detected in each channel by following procedure: signals were filtered using a third order chebyshev filter tuned between 5 to 20 Hz; after that R peaks occurrence were marked using *engzee segmenter* algorithm implemented on *byosppy* python module [8]; finally R peaks were manually corrected by authors. Analysis time was selected from latest first beat to earliest last of any subject. Each **HRV** was then obtained by interpolating at 0.1 s in between these times as shown on Fig. 1. The use of a single amplifier and same time vector ensures that both signals are aligned which is an essential condition for analysis. Once **HRV** signals are obtained connectivity metrics between signals were assessed.

2.3. Connectivity metrics

The working hypothesis yields that **HRV** signals from subjects during sympathetic conversation will achieve larger values on connectivity metrics. In this work, four metrics were used:

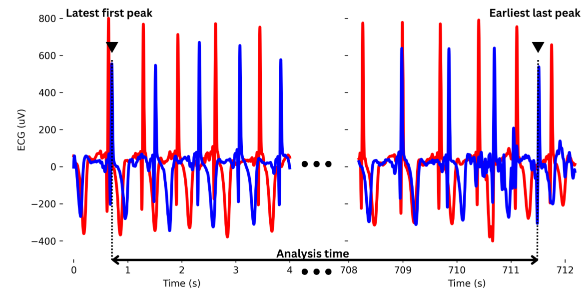

Figure 1. Analysis time definition for signal processing. **HRV** signals were interpolated from **Latest first peak** to **Earliest last peak**. In this example both time marks corresponds to the same subject, but it is not a rule in every recording.

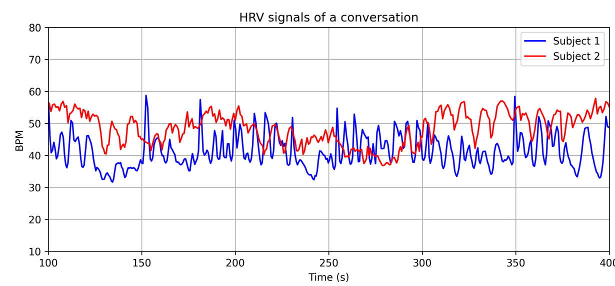

Figure 2. Example of 400 s of HRV signals after interpolation resampling. This is from a sympathetic conversation.

Coherence (***COH***) [9] Is a ratio between between expected value of the cross spectrum between square root of individual spectra, it measure synchrony between both signals.
Phase Lag Index (***PLI***) [10] Measure asymmetry between signals ranging from 0 for a complete random phase difference to 1 for a consistent phase difference.
Weighted Phase Lag Index (***WPLI***) [11] It is an improved method that reduces false synchrony detection induced by noise.
Phase Locking-Value (***PLV***) [12] It is a similar measure to evaluate synchrony based on spectrum, but it is focus on phase different from **COH** that also considers amplitude .

These indices assume that the signals exhibit synchrony, quantified through frequency-based connectivity metrics. Therefore, it is essential that the signals share a common time vector—a condition ensured by the applied signal processing methods. Figure 2 presents an example of synchronized **HRV** signals used for the evaluation of connectivity metrics.

Finally for statistical analysis, given the low number of conversations in each group, a non-parametric permutation analysis was performed over 10,000 iterations using the

Mann–Whitney U test applied to the group medians. This procedure was conducted for each of the four indices, and the corresponding *p-values* were computed.

3. Results

Table 1 presents the numerical values for each of the assessed connectivity metrics, expressed as mean and standard deviation (in parentheses). In addition to the permutation analysis, a standard two-sample *t*-test was performed between groups, and the corresponding results are also reported in the table.

Notably, the mean values for the **sympathy** group were higher across all metrics compared to the **antipathy** group. However, the standard deviations were consistently larger in the **antipathy** group, indicating greater variability.

While both **WPLI** and **COH** yielded values approaching 1, **PLV** and **PLI** produced values closer to 0, suggesting weak or absent connectivity between signals. These results may be attributed to the influence of interpolation artifacts and the high sensitivity of **PLV** and **PLI** to noise. Moreover, these metrics are known to be affected by non-stationarities, which are inherent to **HRV** signals.

index	**sympathy**	**antipathy**	*p-value*
WPLI	0.918 (0.018)	0.644 (0.377)	0.021*
PLV	0.197 (0.033)	0.179 (0.059)	0.897
COH	0.916 (0.024)	0.681 (0.275)	0.034*
PLI	0.023 (0.005)	0.020 (0.003)	0.122

Table 1. Mean values for each of the four connectivity metrics estimated. In each cell mean value and standard deviation in parenthesis are presented. Fourth column show *p-value* for a simple t-test comparison between groups and marked with an asterisk (*) which obtained $p < 0.05$.

The permutation-based statistical analysis revealed that only **COH** ($p = 0.0176$) and **WPLI** ($p = 0.05$) showed significant differences between groups, which is consistent with the results from the simple group comparison. Figure 3 illustrates the distribution of these metrics, highlighting that some conversations in the **antipathy** group still reached values close to 1 for both **COH** and **WPLI**. This observation is noteworthy, as it suggests that even in contexts of disagreement, physiological signals may exhibit synchrony or connectivity.

4. Discussion and Conclusions

The connectivity analysis suggests that social interaction may modulate the physiological processes involved in heart beat occurrence. This modulation could be linked to respiratory dynamics, as the experimental setting fo-

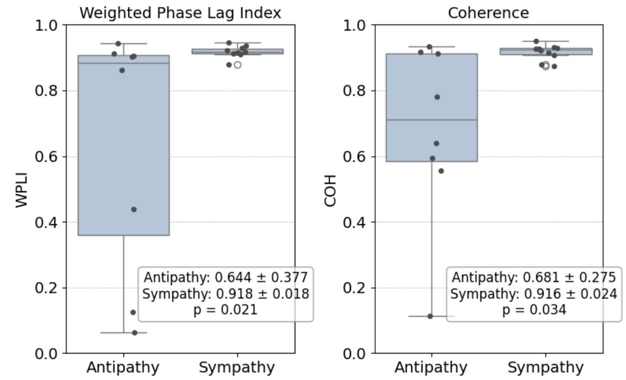

Figure 3. Boxplots of connectivity metrics **WPLI** (left) and **COH** (right). These distributions are shown because achieved a $p < 0.05$ on simple test. Permutation analysis achieved $p < 0.05$ only for **COH**.

cused on spoken conversations. During dialogue, speakers typically alternate turns, resulting in rhythmic patterns of inhalation and exhalation. Interestingly, this turn-taking behavior may persist even during disagreement, such as in debates or conflicts, where participants still take turns speaking—potentially maintaining some degree of physiological synchrony. However, in other forms of disagreement, particularly when individuals disengage or ignore each other, this coordination may break down. Such variations could explain the broader range and lower average connectivity values observed in the **antipathy** group. A more detailed analysis of each conversation is necessary to clarify and support these hypotheses.

Previous studies using fNIRS signals have shown that certain cortical areas become synchronized during listening tasks [2]. These findings suggest that breathing is not the primary driver of this synchrony; however, the experimental conditions in those studies differ substantially from the current work. An alternative explanation for the synchrony observed in the **HRV** signals may involve the activation of cortical autonomic networks (CAN) or subcortical structures such as the amygdala, which are known to influence heart rate [5]. Nonetheless, confirming this hypothesis would require more sophisticated experimental designs and multimodal measurements.

In this study, the metrics employed are based on synchrony between signals assessed through frequency-domain analysis. Although these measures are more robust to noise than simple correlation, they primarily capture time-based synchrony. To better understand the directionality of interaction, additional analyses of causality are needed—for example, to determine whether one **HRV** signal is driving or following the other. Extending such analyses could offer valuable insights into larger-scale social interactions, such as those occurring in classrooms or concerts, where synchrony may emerge as a collective property.

While the underlying causes of physiological synchrony remain unclear, connectivity analysis based on **HRV** has shown promise as an objective tool for assessing social interaction. Although these metrics are commonly interpreted as reflecting connectivity, it is important to clarify that they do not imply direct physical or psychological linkage. Rather, they may reflect self-regulatory processes within each individual, whereby autonomic activity—such as heart rate—dynamically adapts in response to the ongoing social context, leading to emergent synchrony between interacting individuals.

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