Computational methods for the assessment of empathic synchrony

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Abstract. The synchronization of physiological signals between persons is a well-known proxy of empathy. However, it is also influenced by physiological and environmental factors that should be discriminated to correctly characterize the empathy component. We discuss a framework to compute synchrony and introduce *physynch*, an open-source package developed to easily replicate its computational procedures. We adopted *physynch* to study the synchrony of the electrodermal activity in 61 male-female dyads with different types of relationship: strangers (18 dyads), friends (23 dyads) and lovers (20 dyads). The findings confirm previous results on Heart Rate Variability synchrony and suggest that synchrony is influenced by the type of relationship and is stronger in dyads of strangers. *physynch* is made available for download and use for researchers interested in measuring physiological synchrony.

Keywords: empathy, physiological synchrony, relationship

1 Introduction

Empathy between individuals is modulated by both the influence of behavioral reciprocity (e.g. facial expressions [22]) and autonomic physiological response (e.g. heart rate pattern) [3, 14]. Empathy is a key construct in the development of prosocial behavior [8, 26], with effects on cognition [14].

Although fundamental to the study of social behaviour, the assessment of empathy is hurdled by difficulties of its quantification. One of the main approaches is the study of synchrony. Synchrony, defined as the "dynamic and reciprocal adaptation of the temporal structure of behaviors and shared affect between interactive partners [17], is one of the ways in which empathy is manifested and studied [27]. From a computational point of view, we could say that synchrony is the expression of empathy in the time domain, and, as such, can be studied through the analysis of time-related measures, or signals. Typically, studies focus on the synchrony of physiological signals, which are a proxy of autonomic responses [19].

Synchrony first manifests within the context of the mother-infant relationship [1, 10], but instances of synchrony have also been demonstrated in adult dyads. For instance, hormonal association in romantic couples has been linked to empathy [24] and of connectedness [21]; in dyads of strangers the physiological synchrony was correlated with more efficiency in collaborative tasks [7, 22] and cooperation [20].

In this study, we aim at providing general computational guidelines to study empathic synchrony. We discuss the framework proposed by Golland and colleagues [12, 13] to discriminate between different sources of physiological synchrony. Finally, we introduce `physync`, a Python package that implements Golland's framework. We demonstrate the approach on a dataset of electrodermal (EDA) signals to study the effects of emotions and type of relationship on synchrony in male-female dyads.

2 Computational methods to assess empathy

The first issue in studying physiological synchrony to assess empathy is the choosing of an appropriate mathematical framework of reference. Several types of mathematical frameworks have been used in the literature to quantify synchrony between physiological signals, such as cross correlation [12], recurrence plot analysis [20], wavelet coherence [2], Granger causality [18] and others.

The choice of framework should not be arbitrary as each framework has been developed with a specific aim and reference theory. The researcher should choose based on an understanding of the framework's underlying theory, implicit restrictions (e.g. minimum number of samples) and assumptions (e.g. normality of the data). In addition, the computational parameters should be adequately set after a full understanding of their meaning and implications on the results.

The second issue is associated to the need to discriminate between different sources of synchrony. In general, information carried by physiological signals originate from several sources:

1. *Physiological homeostasis*: effect of different functions simultaneously fulfilled by the human body to remain healthy and efficient (e.g. the thermal regulation, the metabolic activity, etc);
2. *Autonomic response*: the Autonomic Nervous System (ANS) controls the functions of bodily organs to enable them to react to external factors (e.g. fight-flight response). In a psychology experiment on synchrony, the external factors are set by the design of the experiment which could be tasks to be accomplished or a series of stimuli;
3. *Empathy*: being in the presence of one or more individual(s) might affect the way the ANS modulates physiological responses to the stimuli [11].

When studying empathy, it is important to discriminate the different sources that contribute the observed physiological synchrony. In particular, the main concern is in the discrimination between the effects of experimental factors and of empathy. Variations due to physiological homeostasis have a low frequency dynamic and are not expected to influence the measures during short term experiments.

To this aim, Golland and colleagues [12, 13], who studied the effect of co-presence on the synchronization of autonomic signals, proposed the computation of three types of synchrony (see Figure 1):

- Co-presence synchrony: between components of the same dyad; influenced by both emotional empathy and by effects induced by the experimental task;
- Task-driven synchrony: between components of different dyads; thus, influenced only by the experimental task;
- Surrogate synchrony: between surrogate signals, and, thus, only due to random factors. Surrogate signals are generated by application of Iterative Amplitude Adjusted Fourier Transform (IAAFT) algorithm. [25].

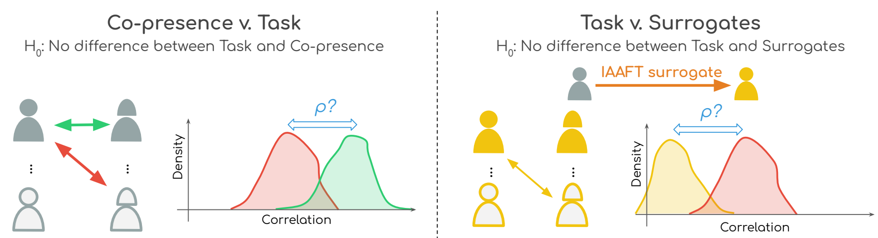

Fig. 1. Golland's framework to discriminate between sources of synchrony in the study of empathy.

The distributions of the three types of synchrony measures are then compared by means of appropriate statistical tests to assess the significance of the effects of the stimuli compared to random factors, and then of the effects of co-presence compared to stimuli. A significant difference between surrogate synchrony and control synchrony serves to reject the null hypothesis that the stimuli have no effects on the physiological response. A significant difference between control and co-presence synchrony serves to reject the null hypothesis that there are no effects due to empathy. Usually, it is expected that both stimuli and empathy increase physiological synchrony, and this should be checked in the post-hoc analysis of the median values of the three distributions. For synchrony metrics, Golland and colleagues used the maximum value of the cross-correlation within a time lag of 10 seconds which allows for delays in the synchrony of the physiological signals. However, the proposed framework is independent of the synchrony metrics adopted.

We developed an open-source Python package, *physynch*[3] (v0.1, Python 3.7), to allow the computation of synchrony of physiological signals within the framework proposed by Golland and colleagues.

[3] https://gitlab.com/abp-san-public/physynch

Its main function, *compute_golland_synch()*, automatically computes the three types of synchrony based on several types of synchrony metrics. Currently implemented metrics are: Dynamic Time Warping, Cross Correlation (CC), Mutual Information, Pearson's and Spearman's Correlation. In addition to the three types of synchrony, it also computes inter-group synchrony: given dyads composed of individuals coming from two categories (e.g. males-females, mothers-children), inter-group synchrony is computed between all the individuals of the same category, thus measuring the effect of the stimuli on the category.

3 Material and Methods

The computational methods discussed in the previous section are demonstrated on physiological signals collected during an experiment to study the effects of emotions and type of relationship on synchrony in male-female dyads (see Figure 2).

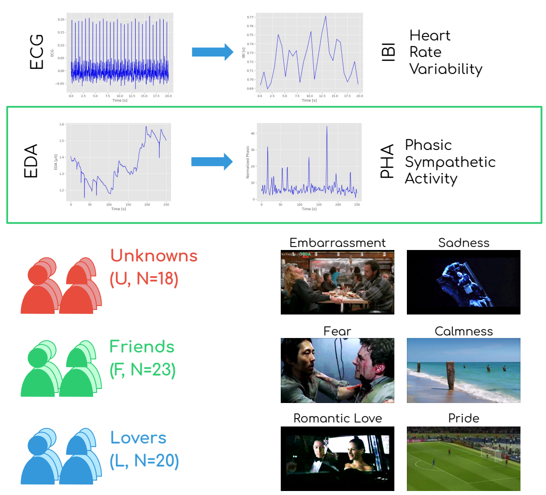

Fig. 2. Representation of the experimental design. Top: two physiological signals were collected: ECG and EDA; the latter is analysed in this study. Bottom: two experimental factors are investigated namely the type of relationship between dyadic members and the type of emotion. Six frames from the six video stimuli are shown.

We studied empathy in 62 male-female dyads divided into 3 groups: Strangers (S, N=18), Friends (F, N=23) and Lovers (L, N=20). The average ages for the 62 female and 62 male participants were 21.65 (SD = 2.77) and 23.48 years old (SD = 5.57), respectively. Participants were distributed in 62 opposite-sex pairs. Participants were recruited among the students of the University of Trento, Italy;

all participants were Caucasian, and none presented with any medical or developmental condition. They were required to provide informed consent before the commencement of the study which was conducted in accordance with the Declaration of Helsinki. Every dyad was exposed to six 4-minutes-long video clips, selected to elicit six different emotions in this fixed order: embarrassment, sadness, fear, calmness, love, pride. The six clips were selected from a set of 20 in a pilot study, in which 10 participants associated each video to a unique emotion. The six videos with most consistent elicited emotions were selected. We acquired the ECG and EDA signal (2048 Hz, FlexComp, Thought Technology) from each subject. In this study, we focused on the EDA, from which we extracted the phasic response (PHA) (see Figure 3), which is linked to the sympathetic activity of the ANS [4]. Before each stimulus, a 10-sec image depicting the title of the video clip on a white background was presented. Between two stimuli, an interval of 1 min with a white fixation point on a green background allowed the participants to return to baseline state. At the end of the last clip, participants were asked to self report three items on a 7-point Likert scale on whether each video was unpleasant/pleasant, scary/funny, embarrassing/non-embarrassing, then a set of instructions would appear on the screen to inform participants that the session had ended. The experimental session lasted 30 min in total.

The EDA signal was first downsampled to 8 Hz, then we removed the spikes and applied a low-pass Infinite Impulse Response filter (pass-band: < 2 Hz, stop-band > 3.5 Hz) to remove high frequency noise. The filtered signal was deconvolved using a Bateman function, and the phasic component was estimated, as described in [4]. The local range of the phasic component was then computed from consecutive non-overlapping portions (length 1 s), resampled at 2 Hz, and used as the continuous index of sympathetic activity (see a representation of the pipeline with the results of the intermediate steps in Figure 3). The processing of the signals was performed with custom scripts based on pyphysio [6] (v2.1, Python 3.7).

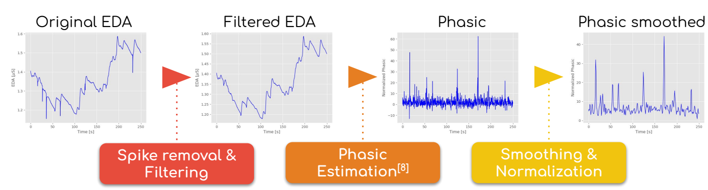

Fig. 3. Signal processing pipeline to extract the Phasic response associated to the sympatethic activity.

We then used *physynch* to compute the three types of physiological synchrony on the PHA signals, using the maximal CC within a time shift of $\pm 1s$, as synchrony metrics [12, 13].

4 Results

We focused here on the results of synchrony analysis of EDA signals (see Figure 4). The results of the analysis of the self-assessment of the perceived emotions, the synchrony of the ECG signal and the effect of gender and type of relationship are part of another study which is separately reported.

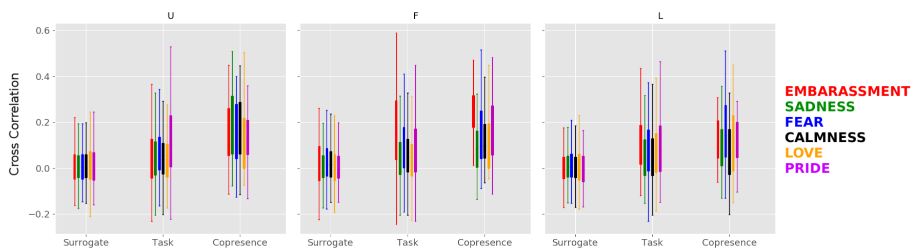

Fig. 4. Values of the physiological synchrony for each group and emotion.

The significance of the differences between the three types of synchrony (see Table 1) in the distributions was assessed with the Mann-Whitney U test as the number of values in distributions of the three synchrony types are different.

The analysis revealed an effect of the task on the synchrony measures for all groups and videos. Effects of co-presence were also found for U and F for all videos, with the exception of the video eliciting pride for the U group, and the video eliciting fear for F. Lovers presented a significant effect of co-presence only for the video eliciting fear.

5 Discussion

Intuitively, we would have expected a stronger co-presence effect where there is an existing social relationship, but this is contradicted by the results on Lovers where the effect of co-presence only emerged in the fear condition. Notably, these findings confirm the results of a previous study on the same dataset which focused on the synchrony of Heart Rate Variability [5].

The results on co-presence effects may seem counter-intuitive; however numerous examples showed that the synchronization of sympathetic response among strangers is common [15, 28] and have been associated to the initiation of affiliation [23] and facilitation of prosocial behaviors [26]. In a recent study that investigated pairs of strangers in competitive, cooperative and naturalistic (i.e. conversational interaction) social contexts, [9] revealed that strangers established physiological synchrony in both the sympathetic and parasympathetic branches of the autonomic nervous system across all social contexts.

Table 1. Summary of the computed synchrony measures and significance of the comparison between the three types of synchrony.

Group	Emotion	Surrogate Mean (SD)	VS	Task Mean (SD)	VS	Co-presence Mean (SD)
Unknowns	EMBARRASS	0.0102 (0.0842)	$p<0.01$	0.0620 (0.1570)	$p<0.01$	0.1719 (0.1972)
	SAD	0.0138 (0.0859)	$p<0.01$	0.0481 (0.1162)	$p<0.01$	0.1695 (0.1743)
	FEAR	0.0114 (0.0820)	$p<0.001$	0.0809 (0.1378)	$p<0.05$	0.1607 (0.2005)
	CALMNESS	0.0156 (0.0865)	$p<0.001$	0.0738 (0.1688)	$p<0.01$	0.1868 (0.2100)
	ROMANCE	0.0230 (0.1084)	$p<0.05$	0.0530 (0.1381)	$p<0.05$	0.1414 (0.1855)
	PRIDE	0.0162 (0.0966)	$p<0.001$	0.1205 (0.1531)	$p=0.24$	0.1351 (0.1330)
Friends	EMBARRASS	0.0186 (0.1045)	$p<0.001$	0.1709 (0.1778)	$p<0.05$	0.2496 (0.1441)
	SAD	0.0091 (0.0777)	$p<0.001$	0.0528 (0.1206)	$p<0.05$	0.1246 (0.2053)
	FEAR	0.0256 (0.0860)	$p<0.001$	0.0954 (0.1299)	$p=0.11$	0.1394 (0.1501)
	CALMNESS	0.0230 (0.0886)	$p<0.001$	0.0758 (0.1576)	$p<0.05$	0.1486 (0.1905)
	ROMANCE	0.0081 (0.0905)	$p<0.001$	0.0467 (0.1129)	$p<0.05$	0.1181 (0.1612)
	PRIDE	0.0142 (0.0894)	$p<0.001$	0.0918 (0.1347)	$p<0.05$	0.1617 (0.1567)
Lovers	EMBARRASS	0.0066 (0.0802)	$p<0.001$	0.1189 (0.1336)	$p=0.36$	0.1313 (0.1324)
	SAD	0.0111 (0.0844)	$p<0.001$	0.0573 (0.1279)	$p=0.14$	0.1089 (0.1875)
	FEAR	0.0147 (0.0820)	$p<0.001$	0.0786 (0.1389)	$p<0.01$	0.1694 (0.1604)
	CALMNESS	0.0172 (0.0928)	$p<0.001$	0.0640 (0.1467)	$p=0.21$	0.1047 (0.2108)
	ROMANCE	0.0139 (0.0913)	$p<0.001$	0.0875 (0.1544)	$p=0.16$	0.1365 (0.2029)
	PRIDE	0.0014 (0.0852)	$p<0.001$	0.0936 (0.1330)	$p=0.58$	0.1001 (0.1089)

These results strongly corroborate with the findings from our present study in which greater physiological synchrony is observed in less substantiated relationships (i.e. pairs of strangers). Overall, physiological synchrony between strangers are postulated to accompany perceptions of similarity which serve to lay the foundation for future social affiliations. Since Lovers have ideally established their relationship with each other, physiological synchrony may not necessarily serve to enhance social "connectedness" within this group. A limitation of this study is that we did not consider the duration and quality of the romantic relationship, and the particular age range of the participants, which may or may not have fallen within the active partner-seeking phase and thus have differing implications [16].

Taken together, these results reveal the importance of adopting an appropriate approach to avoid errors in the computation of physiological synchrony. It is only due to a suitable adopted framework that we could evince the different effects of co-presence in Lovers. Otherwise, we could have mistakenly assumed that Lovers showed synchrony of physiological response, without being able to observe that this was mainly due to the task, and not to the fact that the dyad was watching the video stimuli together.

6 Conclusion

When quantifying empathy through analysis of physiological synchrony, it is critical to account for the different sources of physiological variability. In this paper, we aimed to highlight the framework proposed by Golland and colleagues as an elegant approach to statistically discriminate and assess both the effects of task and co-presence in dyads. To allow other researchers to easily apply the framework, we developed the Python package *physynch*, and demonstrated its use in a study which investigates the effects of the type of relationship and emotion on the synchrony of the sympathetic response. The results showed that the task of watching the same video has an effect on the synchronization of the sympathetic response. However, only in strangers and friends we observe the effect of co-presence.

We encourage the adoption of the proposed framework, made easier by the *physynch* package, to analyse synchrony in different experimental studies. Its use is not limited by the type of signal or synchrony metrics applied and can be therefore adapted to different research questions and contexts.

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