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Analytic approaches for the combination of autonomic and neural activity in the assessment of physiological synchrony*

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Abstract— **Physiological synchrony (PS) refers to the similarity in physiological responses of two or more individuals and may be an informative source of information in the field of affective computing. Up to now, PS has been assessed using either autonomic measures or neural measures. While in literature multiple physiological channels have already been combined into one composite index for PS assessment, multimodal PS, i.e., using a combination of autonomic and neural channels in a single composite index ('A-N' multimodal), has remained unexplored. A-N multimodal PS is promising for the robust detection of emotionally or cognitively relevant events, as both autonomic and neural activity are sensitive to these events. The aim of this study is (i) to review analytic approaches that have been used to combine multiple physiological channels into one composite index for PS, and (ii) to view these approaches in the light of their potential applicability to A-N multimodal PS.**

A literature search was conducted to find studies assessing PS based on a composite index of multiple autonomic channels or multiple channels in electroencephalographic (EEG) recordings. Four studies were found that assessed PS based on a composite index using multiple autonomic channels and 12 studies assessed PS based on a composite index using multiple EEG channels.

We found that analytic approaches varied between studies. Some averaged over multiple channels after assessing PS separately per channel ($N = 4$), or averaged over channels before assessing PS ($N = 1$), while others used different linear combinations of channels based on spatio-spectral decomposition ($N = 1$) or correlated component analysis (CCA, $N = 8$). CCA finds linear combinations of channels that are maximally correlated between subjects and has up to now been used to assess neural PS. We suggest that this method may be most appropriate for the exploration of multimodal PS assessment.

I. INTRODUCTION

Events that are emotionally or cognitively relevant to an individual induce autonomic responses, such as changes in heart rate or electrodermal activity, as well as responses of the central nervous system (brain signals). These responses are often modest and hard to detect at the level of a single event. Detection is especially hard if one does not want to, or cannot rely on prior knowledge of the time that a relevant event occurred, and if one does not want to collect training data in order to train an individually tailored model for detection of (emotionally) relevant events of the user, as is usually done in the area of affective computing or passive brain-computer interfaces [1]. Within the context of monitoring the mental state of groups of individuals, an approach that could deal with these problems is physiological synchrony (PS). PS refers to the similarity in physiological responses of two or more individuals. It has been studied for autonomic activity and neural activity.

Research on autonomic PS started halfway in the 20th century. Researchers started exploring simultaneous physiological data collection from more than one individual with the aim of studying interpersonal interactions [2]. From then onwards, autonomic PS has been used to study interactions between romantic couples, parent-child dyads and teammates, and has been associated with empathy, relationship quality and team-performance [3], [4], [5].

Neural PS was first monitored in the mid-1960s. Duane and Behrendt [6] recorded neural activity from two participants simultaneously in an attempt to show interpersonal physiological communication. Since then, neural PS has, among others, been shown to be a correlate of classroom engagement [7] and a predictor of expressions of interest and preference during popular television content [8].

Up to now, research on PS has either focused on PS in autonomic activity or on PS in neural activity, while multimodal PS, including both types of signals (from now on referred to as 'A-N' multimodal) might be of added value. We found two studies in which neural activity was monitored in parallel with autonomic PS [9], [10]. However, in these studies, neural activity was only recorded in one of the pair of individuals, as the researchers were interested in neural activity of clients during therapist-client interactions during times of high autonomic PS.

Both autonomic and neural responses can distinguish between affective and neutral stimuli across visual and auditory modalities [11], [12], [13], [14] and autonomic and neural responses can both identify stressful situations [15], [16], [17], [18]. Therefore, multimodal synchrony assessment, based on both neural and autonomic channels, could lead to more robust detection of emotionally or cognitively relevant events.

To enable A-N multimodal PS, an overview of analytic approaches that might be suited for the combination of neural and autonomic measures into a single composite index, for which overall PS can be assessed, is needed. PS literature can provide us with methods enabling the combination of multiple physiological channels into one index for PS assessment, that may be used for this aim. Developments in methodological approaches have led to increasingly advanced methods to assess PS. Early studies used zero-order

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correlations between electrodermal activity and heart rate of therapist and client [19], [20], [2]. Since then, more advanced methods have been used to quantify interpersonal PS, such as wavelet analysis or dynamic systems modeling [21], [22], [23]. The combination of multiple autonomic physiological measures into one composite index was also explored, to provide a single measure of PS. Levenson and Gotmann [4] argued that a composite index provides a better test in characterizing the interpersonal physiological relation in a dyad than separate measures of PS. In neural PS studies, electroencephalography (EEG) is typically recorded using multiple electrodes. Researchers have used methods to combine these data streams as well.

Reviews on analytic approaches for PS exist already [24], [25]. They focus on important issues such as how to determine whether observed synchrony is higher than chance. However, they are on assessment of PS between just two channels and do not cover approaches enabling the combination of multiple channels into one composite index. The literature review on autonomic PS from Palumbo et al. [26] includes studies using a composite index for PS assessment. However, Palumbo et al. do not focus on the analytic approaches of these studies, do not include approaches from neural literature and do not view the approaches from included studies in the light of potential A-N multimodal applications. The current literature study is aimed at (i) providing an overview of analytic approaches that are used to combine multiple channels into one composite index for PS assessment, within the field of autonomic PS and within the field of neural PS, and (ii) to view them in the light of their potential applicability to A-N multimodal PS.

II. METHODS

To find analytic approaches used to combine multiple *autonomic* measures into a single composite index for PS assessment, the systematic review on autonomic PS from Palumbo et al. [26] was chosen as a start. This review provides an overview of studies monitoring autonomic PS, published in peer-reviewed journals before November 2015. Studies using a composite index for PS assessment (see Appendix F in [26], which summarizes studies according to physiological measures, context, findings, and results) were reviewed in the present study. Studies were included if interpersonal PS was assessed using a composite index based on more than one autonomic measure. References of the included studies and citations in the included studies were also reviewed.

For providing an overview of the analytic approaches used to assess *neural* PS, a systematic search was conducted. The goal of this search was to find a comprehensive, but representative sample of studies that monitored multi-channel EEG of multiple participants and assessed their interpersonal PS using a composite index. Using Scopus, a search was conducted with the following search terms.

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TITLE-ABS-KEY((brain-to-brain OR interbrain
OR inter-brain OR hyperbrain OR intersubject
OR inter-subject) AND (electroencephalogra*
OR eeg) AND (synchron* OR correlation OR
coupling))
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Based on title, abstract and keywords, studies were only selected if neural PS between multiple human subjects was assessed using a composite index based on multi-channel EEG. The literature study was performed in February 2019.

III. RESULTS

A. Approaches from autonomic literature

From the 61 studies reviewed in [26], only three studies assessed PS based on a composite index. Others only measured one physiological channel ($N = 38$) or measured more than one physiological channel, but assessed PS separately per channel ($N = 20$). After reviewing references in the included studies and citations of the included studies, one more study using a composite index was included, resulting in four studies in total. Table I summarizes the studies according to purpose, sample, physiological measures, and the composite index.

As shown in the table, the four studies used similar combinations of physiological measures in their composite index. All studies used a measure of cardiovascular activity, three studies used a measure of electrodermal activity and three studies included general somatic activity (body movement). The combination of measures resulted in both sympathetic and parasympathetic measures in all studies.

In two of the included studies [4], [28], the composite index for PS assessment was calculated using a bivariate time-series analysis. All physiological channels were averaged over time within 10 second windows. The z-score of these average values was computed, after which the bivariate time-series analysis, following [27, Chapters 23-25], was performed. For each physiological measure, this analysis provided two chi-square values. These values represented the extent to which the physiological responses from one individual of the couple accounted for the variance in the physiological pattern of their partner, beyond the variance accounted for by the physiological pattern of the partner itself. The z-scores of these values were computed and then averaged over all measures as an overall measure of directional PS in that 10 second time-window. Levenson and Gottman [4] used this to study how PS was associated with marital satisfaction.

Marci [29] combined PS in four physiological channels with the cumulative strength of the overall physiological responses, with the aim to measure audience engagement during television commercials. Unfortunately, it was not described how PS in the four physiological channels was combined into one moment-to-moment time-locked composite index for PS.

Walker et al. [30] aimed to predict team performance in a simulated task by assessing PS between team members, using a multiple regression approach. Team performance was estimated based on task difficulty in the first regression step and based on physiological measures in the second step. The authors described three different approaches. In Analyses 1 & 2, the individual parasympathetic and sympathetic

TABLE I: STUDIES COMBINING MULTIPLE AUTONOMIC CHANNELS INTO ONE COMPOSITE INDEX FOR PS ASSESSMENT.*

Reference	Purpose	Sample	Measures	Composite index
[4]	Determined whether PS could be detected in couples, and whether that was predictive of marital satisfaction.	30 married couples	ACT, EDA, IBI, PTT	Bivariate time-series analysis [27, Chapters 23-25] separately per channel, averaged over all channels.
[28]	Tested whether there was a relationship between PS and perceived empathy.	31 married participants	ACT, EDA, FPA, HR, PTT,	Bivariate time-series analysis [27, Chapters 23-25] separately per channel, averaged over all channels.
[29]	Tested whether PS and arousal level predicted viewers' engagement in advertisements.	27 male viewers in two groups	ACT, EDA, HR, RR	PS was combined with physiological intensity, defined as the cumulative strength of the physiological responses, as a measure of viewer engagement.
[30]	Investigated the relationship between PS and joint team performance in a simulated task.	34 two-person teams	LVET, PEP, RSA	Three regression methods were executed to create a measure of team autonomic activity, using individual, correlated and canonically correlated [31] measures of sympathetic and parasympathetic activity respectively.

ACT = general somatic activity (body movement), EDA = electrodermal activity, HR = heart rate, IBI = inter-beat interval, LVET = left ventricular ejection time, PEP = pre-ejection period, PTT = pulse transmission time, RR = respiration rate, RSA = respiratory sinus arrhythmia.
*Parts adapted from [26]

measures were used, respectively, to estimate team performance. In Analyses 3 & 4, the normalized parasympathetic and sympathetic measures were correlated between team members, producing a team parasympathetic score and a team sympathetic score. In Analysis 5, the parasympathetic and sympathetic scores were combined and correlated, using canonical correlation [31].

B. Approaches from EEG literature

Using the search terms described above, 170 studies were found. From these studies, 12 studies that met the inclusion criteria were selected. Table II summarizes them according to purpose, sample, number of channels and the composite index.

The most simple approach that was followed in order to combine multiple measures in one composite index is to average over multiple channels after assessing synchrony separately per channel. In a study on neural PS in students following classes with different teaching styles, Dikker et al. [7] employed a method called total interdependence TI [35]. Magnitude squared coherence was computed using the Welch method for six one-to-one paired electrodes from two subjects. TI for one pair of subjects was then obtained by averaging over all six electrodes and subject-to-group TI was obtained by averaging over all pairwise combinations of one subject with the other subjects. To validate if TI reflects attention to external stimuli, student-to-group TI values were compared between auditory tones and teaching styles with a single-source auditory input (e.g., lecture or reading aloud), hypothesizing that values would be similar. Student-to-group TI was numerically similar in response to tones as in response of the single-source teaching styles.

Lindenberger et al. [38] selected two synchronization measures to study PS in pairs of guitarists: the phase locking index, as a within-brain phase synchronization measure, and interbrain phase coherence (IPC), as a between-brain phase synchronization measure. EEG time series divided into 3 s epochs were transformed into a complex time-frequency signal, for frequencies up to 20 Hz, using a complex Gabor expansion function. IPC values from six fronto-central electrode pairs were averaged in time-frequency domain as measures of PS. Mean IPC values three standard deviations above baseline were considered as statistically significant.

PS of a composite index can also be quantified by averaging over channels before assessing PS. Kinreich et al. [37] computed the Spearman correlation over the time signal of the Stockwell transform frequency spectrum, for each frequency bin, averaged over electrodes within regions of interest (frontal, parietal, temporoparietal, occipital) in two romantic partners and compared this to stranger-dyads. The dyadic correlation values for each frequency bin and region of interest were averaged over two groups (partners and strangers).

Other linear approaches have also been explored. Zamm et al. [42] reduced the dimensionality of the multi-channel EEG recordings to a single dimension using spatio-spectral decomposition (SSD) [43], which is a linear spatial decomposition filter. SSD finds a linear filter that maximizes the variance of the signal at peak frequency, while minimizing the variance of the noise at the neighboring frequency bins. After spatial filtering, correlations between the amplitude envelopes of two pianists were calculated as a measure of PS. The observed correlations were compared with a chance distribution of white-noise correlations and observed amplitude envelope correlations were found to be higher than the 95% chance estimates.

Eight studies [33], [8], [36], [32], [39], [41], [34], [40] evaluated intersubject correlation based on correlated component analysis (CCA) [33]. The method was designed to find linear combinations of channels that are maximally correlated in time, to identify distributed sources of neural activity. Formally, the approach seeks to maximize the Pear-

TABLE II: STUDIES COMBINING MULTIPLE EEG CHANNELS INTO ONE COMPOSITE INDEX FOR PS ASSESSMENT.

Reference	Purpose	Sample	No. channels*	Composite index
[32]	Determined the conditions under which multisensory stimulation would benefit or hinder the retrieval of everyday experiences, with PS as a marker of enhanced stimulus processing.	88 participants	64	CCA [33], linear combination of channels resulting in maximum ISC
[34]	Investigated whether similarity of EEG responses across subjects to educational videos would be a sensitive measure of knowledge acquisition.	39 participants	64	CCA [33], linear combination of channels resulting in maximum ISC
[7]	Identified whether PS could be a neural marker of group engagement during dynamic real-world group interactions.	12 students	6	Averaged over all channels after calculating PS separately per channel using TI [35]
[33]	Identified brain areas marked by high levels of correlation within and between subjects, evoked by short film clips.	20 participants	64	CCA, linear combination of channels resulting in maximum ISC
[8]	Investigated whether PS was predictive of expressions of interest and viewership during a popular television series.	16 participants	64	CCA [33], linear combination of channels resulting in maximum ISC
[36]	Explored whether PS would predict attentional engagement to a naturalistic narrative stimulus.	76 participants	64	CCA [33], linear combination of channels resulting in maximum ISC
[37]	Compared PS during a male-female naturalistic social interaction between romantic couples and strangers.	24 romantic couples & 25 stranger dyads	32	SC between SP was averaged over channels, after which dyadic correlation values were computed.
[38]	Investigated PS in pairs of guitarists playing a short melody together.	8 pairs of guitarists	16	PLI and IPC values from six fronto-central electrode pairs were averaged in time-frequency domain.
[39]	Investigated whether PS as a measure of auditory attention could distinguish between patients and healthy controls.	20 participants with disorders of consciousness & 14 controls	37	CCA [33], linear combination of channels resulting in maximum ISC
[40]	Investigated whether PS to naturalistic video stimuli decreases with maturity as a marker of neural development.	114 participants (main) & 202 participants (replication)	105	CCA [33], linear combination of channels resulting in maximum ISC
[41]	Determined whether student PS can be quantified in a real-time manner based on portable EEG recordings in a classroom.	28 participants in 4 groups	14	CCA [33], linear combination of channels resulting in maximum ISC
[42]	Explored PS between two pianists performing a musical duet.	1 pair of pianists	24	Channels were combined using SSD [43], after which amplitude envelope correlations were calculated.

CCA = correlated component analysis, IPC = interbrain phase coherence, ISC = inter-subject correlations, PLV = phase locking value measure, PS = physiological synchrony, SC between SP = Spearman correlation between spectral powers, SSD = spatio-spectral decomposition, TI = total interdependence.
*Represents the No. of channels used in the composite index for synchrony assessment, not the total No. of monitored channels.

son Product Moment Correlation Coefficient. CCA is similar to the more familiar principal component analysis, as both methods project data on a common subspace, except that projections of CCA capture maximal correlation between datasets instead of maximal variance within a dataset. To obtain a measure of subject-to-group PS, data from a single subject was projected on the component vectors. Then, PS of the group was calculated as the correlation coefficient of these projections separately for each component and averaged over all possible subject-pairs involving a single subject. The result is a time-locked, moment-to-moment measure of PS. To check the significance of the correlated components, Dmochowski et al. [33] employed a permutation test approach [44]. Correlations were computed with a data set of which 5 s blocks were randomly shuffled in time. The three component correlations were significantly larger than chance levels for 33%, 23% and 10% of movie time for a short, arousing film clip. Similar, Cohen and Parra [32] compared PS of the correlated components to PS in 100 phase-randomized surrogate data-sets [45]. The first three components were selected, as correlations in the weaker components were not always significantly different from chance levels.

IV. DISCUSSION

This literature study was aimed at (i) providing an overview of analytic approaches that are used to combine multiple physiological channels into one composite index for PS assessment and (ii) to view them in the light of their potential applicability to A-N multimodal PS, which will be done below.

Both for autonomic channels and neural channels, PS is most often assessed separately per channel, if multiple channels are assessed at all. The analytic approaches that are used to combine multiple channels in a composite index vary in complexity and potential suitability for A-N multimodal applications. The simplest indices average over multiple physiological channels after assessing PS separately per channel, such as [7], [4], [28], [38], or average over multiple physiological channels before assessing PS, such as [37]. Averaging over multiple channels can be advantageous, for example to assess synchrony based on multiple electrode readings within a region of interest of the brain or to obtain an overall measure of brain-to-brain synchrony. However, when stimulus-response latency varies strongly between variables, averaging over multiple physiological channels is not appropriate. This is the case when neural and autonomic measures would be considered. For instance, neural event-related potential latencies are in the order of tens or at most a few hundreds of ms, while response latency exceeds 1000 ms for skin conductance responses [46].

Other linear combinations of channels are not all suited for A-N multimodal applications either. Zamm et al. [42] reduced multi-channel EEG to a single dimension using SSD, which maximizes variance at peak frequency, while reducing variance in neighboring frequency bins. As the frequency power spectrum varies greatly between autonomic and neural measures, SSD is not appropriate for A-N multimodal applications.

The CCA [33], on the other hand, seems appropriate for the exploration of A-N multimodal PS. Data is projected on a subset of data for which intersubject PS is maximized. The method itself thus selects the appropriate linear combination of channels that maximize PS across subjects. This can be especially useful for exploration of mixed neural and autonomic channels, where it might not be known if or how strong each channel synchronizes across participants. If channels of interest are a-priori known, simpler aggregations of channels might be more suited. Note that for a small number of participants, CCA could lead to misleading results, as it could provide a subset of data that maximizes PS only within the small population. However, the observation that neural PS in a small sample of participants predicted expressions of interest of the larger audience with higher accuracy than the expressions of interest of the small sample [8], suggests that CCA can provide valid results even for small samples of participants. Our next step is to exploit and test this method to analyze an A-N multimodal dataset we recently collected from participants who were presented with the same audio but differed in attentional focus.

We end by noting two limitations of the current literature review. Firstly, we did not do a targeted search for combining multiple autonomic and/or neural measures in intra-person synchrony. Such a search may still provide new insights as to methodology to reach A-N multimodal composite indices for PS assessment. Secondly, for neural measures, the current literature review only examined analytic approaches used to assess multi-channel electroencephalographic PS. Analytic approaches used for assessing PS monitored with other neuroimaging techniques, such as functional magnetic resonance imaging (fMRI) or magnetoencephalography (MEG), might also be suited for A-N multimodal applications.

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