Shared attention reflected in EEG, electrodermal activity and heart rate

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***Abstract*— Monitoring directed auditory attention in groups can be helpful in a range of contexts. Concurrent change in physiological variables across multiple listeners (physiological synchrony – PS) may be a suitable marker of attentional focus as caused by shared affective or cognitive processes. We here determine PS for EEG (electroencephalography), EDA (electrodermal activity) and heart rate in participants who were instructed to either attend to an audiobook (n = 13) or to interspersed auditory events (n = 13) such as emotional sounds, and beeps that attending participants needed to keep track of. Even though all participants heard the exact same audio track, for both EEG and EDA, PS was higher for participants linked to participants in their own attentional group than to participants in the other attentional group. No such effect was found in heart rate. For a single individual, EEG PS allowed attribution to the correct attentional group in 85% of the cases, for EDA this was 81%. Hearing is not the same as attending - our results are promising for monitoring group affective and cognitive processes and how an individual relates to that.**

Keywords*— *attention, affective, cognitive, EEG, EDA, ECG, heart rate, skin conductance, auditory, group

I. INTRODUCTION

We are interested in tools that enable continuous monitoring of cognitive or affective processes, without requiring conscious action of the monitored individuals. Information about attention in a group of individuals, or how attention in a certain individual relates to attention in other individuals, may be useful to study and support children in an educational setting who suffer from attentional problems, or helpful to evaluate and design effective educational material.

Continuous and implicit measures of attention may be extracted from physiological signals. For instance, in a series of similar stimuli, a deviant that automatically draws attention generates a P3 peak in electroencephalography (EEG) [1]. Not only bottom-up, but also top-down, 'self-determined' attention to events elicits attention-related evoked potentials in EEG [2] [3]. Emotional stimuli have been shown to affect physiological measures, such as electrodermal activity (EDA) and heart rate [4] [5] and cognitive working memory tasks induce changes in a range of physiological measures as well [6]. While the physiological responses elicited by emotional stimuli and mental tasks do not reflect (only) attention, these processes are expected to be associated with attention, and hence are of interest when one is interested in monitoring attention.

In most research on physiological measures of cognitive and affective processes, measures are extracted after relating physiological signals to the time that stimuli of interest occur, i.e., stimuli that are expected to elicit the cognitive or affective state of interest. In real-life contexts, this is difficult to do from a practical point of view. In addition, it is often not clear what the stimulus of interest is. When studying groups, a solution to this is to determine the degree to which physiological measures of multiple people uniformly change (physiological synchrony -PS). Highly similar physiological responses, i.e., high PS, would indicate shared attention to an apparently generally relevant event. [7] showed that moments of high synchrony in EEG signals between viewers of a popular television series co-occurred with interesting events, and predicted the expressions of interest and attention to the television series, as measured by viewership. [8] showed that synchrony in EEG signals between students in a classroom predicted class engagement and classroom dynamics, a relationship that may be driven by shared attention in a group. [9] presented participants with the same auditory or audiovisual stimulus, but instructed them to either attend to this stimulus, or to perform an unrelated mental arithmetic task throughout the duration of the stimulus. They showed that EEG PS differed between these conditions. There is also a body of literature on synchrony in peripheral physiological measures such as heart rate and EDA (reviewed by [10]). Rather than as indicators of shared directed attention (and hence, shared affective and cognitive processes), these have been more generally interpreted as indicators of some form of connectedness between people. Up to date, PS literature on neural and peripheral physiological signals have remained separate.

In the current study we compare PS in neural and peripheral physiological variables to determine differential attentional focus of individuals who are all presented with the same stimulus, and are all attending to it, be it to different stimulus aspects. Reminiscent to a classroom setting where students hear the teacher talk as well as hearing other auditory potentially interesting events, we present our participants with the same auditory stimulus, consisting of an audiobook, interspersed with short stimuli. Participants are instructed to attend to either the audiobook narrative, or to the short stimuli. We hypothesize that EEG, EDA and heart rate recordings of participants are more strongly synchronized with those of participants in the same attentional condition compared to the other attentional condition. To the best of our knowledge, this is the first study that examines synchrony in multiple neural and peripheral physiological measures, and the extent to which these measures distinguish between

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groups of individuals with a different auditory attentional focus.

II. METHODS

A. Participants

We recorded from 27 participants (aged between 18 and 48) with no self-reported problems in hearing or attention. Participants were recruited from the participant pool of TNO (the research institute where the study was conducted). Prior to the experiment all participants signed an informed consent form and after the experiment they received a small monetary award for their time and travelling costs. Data of one participant was discarded due to failed physiological recordings. The study was approved by the TNO Institutional Review Board (TCPE) and the TU Delft Human Research Ethics Committee.

B. Materials

EEG, EDA and ECG (electrocardiogram) were recorded using an ActiveTwo system (BioSemi, Amsterdam, Netherlands) at 1024 Hz. EEG was recorded with 32 active Ag-AgCl electrodes, placed on the scalp according to the 10-20 system, together with a common mode sense (CMS) active electrode and a driven right leg (DRL) passive electrode for referencing. Electrode impedance threshold was set at 20 kOhm. For EDA, two passive gelled Nihon Kohden electrodes were placed on the ventral side of the distal phalanges of the middle and index finger. For ECG, two active gelled Ag-AgCl electrodes were placed at the right clavicle and lowest floating left rib. EDA and heart rate were also recorded using wearable systems. These data will be discussed elsewhere.

C. Stimuli and Design

Each participant listened to the same audio file, composed of a 66 min audiobook (a Dutch thriller 'Zure koekjes', written by Corine Hartman) interspersed with other auditory stimuli. Intervals between these short stimuli varied between 35 and 55 seconds. Half of the participants were asked to focus on the narrative of the audiobook and ignore all other stimuli or instructions; and half of the participants were asked to focus on the other stimuli and perform accompanying tasks, and ignore the narrative. The auditory stimuli were emotional sounds, beeps, and the instruction to sing a song. The order of sounds and beeps was randomly determined.

Emotional sounds were taken from the IADS (International Affective Digitized Sounds – [11]). The IADS is a collection of acoustic stimuli that have been normatively rated for emotion. Examples of stimuli are the sound of a crying baby or a cheering sports crowd. We selected 12 neutral sounds (IADS number 246, 262, 373, 376, 382, 627, 698, 700, 708, 720, 723, 728), 12 pleasant sounds (110, 200, 201, 202, 311, 352, 353, 365, 366, 367, 415, 717) and 12 unpleasant sounds (115, 255, 260, 276, 277, 278, 279, 285, 286, 290, 292, 422). Sound duration was 6 seconds.

Beeps were presented in blocks of 30 seconds, with every two seconds a 100ms high (1kHz) or low (250Hz) pitched beep. Short-stimuli attending participants needed to separately count the number of high and low tones [12]. This task was practiced with them beforehand. In total, 27 blocks of sounds were presented.

At the end of the audiobook, the instruction was presented to sing a song aloud after the subsequent auditory countdown reached 0. This instruction had to be followed by the short-stimuli attending group and was expected to induce stress [12].

Finally, participants filled out a questionnaire in which they were asked to report as many emotional sounds as they could remember, to estimate the average number of high and low beeps in a sequence, and questions about the content of the narrative.

D. Analysis

Data processing was done using MATLAB 2018b software (Mathworks, Natick, MA, USA).

EDA was downsampled to 64 Hz. The phasic component of the signal was extracted using Continuous Decomposition analysis [14] as implemented in the Ledalab toolbox for Matlab.

ECG measurements were processed to acquire the inter-beat interval (IBI – the inverse of heart rate). After downsampling to 256 Hz, ECG was high-pass filtered at 0.5 Hz. Peaks were detected from a squared version of the reconstructed frequency-localized version of the ECG waveform using wavelets [15]. The IBI semi-time series was transformed into a timeseries. This was done by interpolating consecutive IBIs and then resampling at 2 Hz.

EEG was processed offline with EEGLAB v14.1.2 for MATLAB [16]. EEG was first downsampled to 256 Hz, high-pass filtered at 1 Hz and notch filtered at 50 Hz, using the standard FIR-filter implement in EEGLAB function pop_eegfiltnew. Channels were re-referenced to the average channel values. Logistic infomax independent component analysis (ICA, [17]) was performed on more strongly filtered data to classify artifactual independent components, i.e., components not reflecting sources of neural activity, but ocular or muscle-related artifacts. These components were removed from the data. Samples whose squared amplitude magnitude exceeded the mean-squared amplitude of that channel by more than four standard deviations were marked as missing data ('NaN').

Similarity of EEG between participants in the time-domain was assessed using correlated component analysis (CorrCA) [18]. CorrCA is similar to the more familiar principal component analysis, except that projections of CorrCA capture maximal correlations between data sets instead of maximal variance within a set of data. Rather than treating EEG channels separately, this analysis results in correlated components. ISC (inter-subject correlation) is determined by the sum of correlations of the first three of these components. See [9] for a detailed description of the procedure that was followed. To discriminate between attentional task conditions, correlated component vectors were extracted from both the narrative and short-stimuli group. Data from each subject was then projected on these component vectors. Correlations between each participant with all other members of the narrative and short-stimuli group were computed. The average correlation between a participant and all participants in the narrative and in the short-stimuli groups are from now on referred to as ISC-narrative and ISC-short-stim. To avoid training biases in the component extraction step, data from the to-be tested subject were excluded in this step.

Similarity of EDA (phasic component) and IBI between participants in the time-domain was assessed using a moving window approach, introduced by [19]. Pearson correlations were calculated over successive, running 15s windows at 1s increments. The overall correlation between two responses was computed as the natural logarithm of the sum of all positive correlations divided by the sum of the absolute values of all negative correlations. As for EEG, ISC-narrative and ISC-short-stim were determined for each participant by determining his or her ISC with each of the members of the narrative group as well as with the short-stimuli group.

Wilcoxon rank sum tests were performed to test for differences in performance with respect to the questions about the auditory stimuli between the two attentional groups. Paired sample t-tests were conducted to test whether ISC-narrative and ISC-short-stim were significantly different within each attentional group for EEG, EDA and IBI.

III. RESULTS

Participants in the narrative group answered more questions about the narrative correctly than participants in the short-stimuli group (Z=2.68, p=.007), whereas participants in the short-stimuli group could name more emotional sounds (Z=2.68, p=.007) and were closer to the actual average number of high and low beeps (Z=2.82, p=.005) than the narrative group. This indicated that participants followed the attentional instruction.

Fig. 1 shows the inter-subject correlation (ISC) averaged across participants of the narrative group (left bars) and the short-stimuli group (right bars) when paired with participants of the narrative group (dark bars) or short-stimuli group (light bars). Data of individual participants are plotted on top of the bars. For EEG (Fig. 1A) ISC is higher for most participants when paired to participants of their own attentional group compared to participants from the other group. This is so both for participants in the narrative group (t12 = 3.57, p = 0.004) as well as the short-stimuli group (t12= -3.57, p = 0.004). For EDA (Fig. 1B), the same pattern of results is observed, but it only reaches significance for the short-stimuli group (t12= -3.932, p = 0.002; narrative group: t12= 0.96, p = 0.357). For IBI (Fig. 1C), the trend is again the same but no significant effects were observed (narrative group: t12 = 0.85, p = 0.413; short stimuli: t12 = -1.37, p=0.196).

When assuming for each participant that she or he follows the attentional instruction as indicated by the group with whom she or he shows the highest averaged synchrony, classification accuracies are significantly higher than chance for EEG and EDA. For EEG, classification accuracy is 85% both for participants from the narrative and from the short-stimuli group. For EDA, classification accuracy is 77% for participants from the short-stimuli group and 85% for the narrative group. For IBI, classification accuracy is not higher than chance in both groups. Chance level was determined by using surrogate data with randomized group labels. Significance levels were determined using 10000 renditions of randomized group labels. An overview of the classification data is presented in Fig. 2.

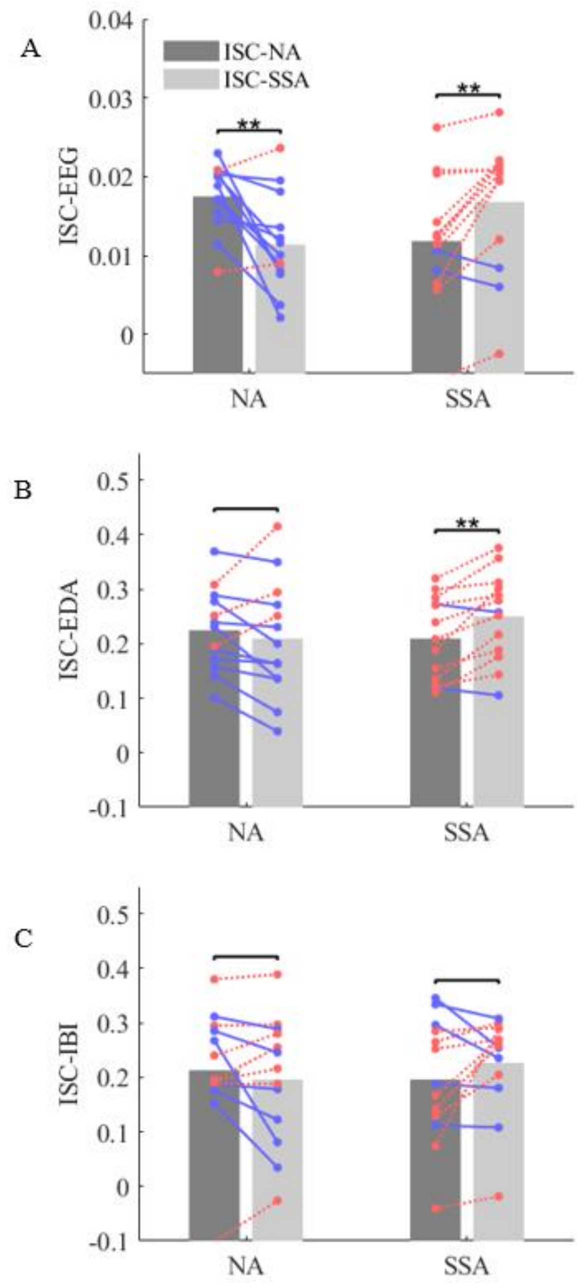

Fig. 1. Inter-subject correlations for narrative-attending participants (NA) and short-stimuli attending participants (SSA) when related to participants of each of the two groups, for EEG (A), EDA (B) and IBI (C). Connected dots display subject-to-group correlations of each of the individual participants, where blue lines indicate individuals for which ISC-NA > ISC-SSA and red, dotted lines indicate individuals for which ISC-SSA > ISC-NA. Paired sample t-tests revealed that within-group correlations were higher than between-group correlations in EEG and EDA (**p < 0.01).

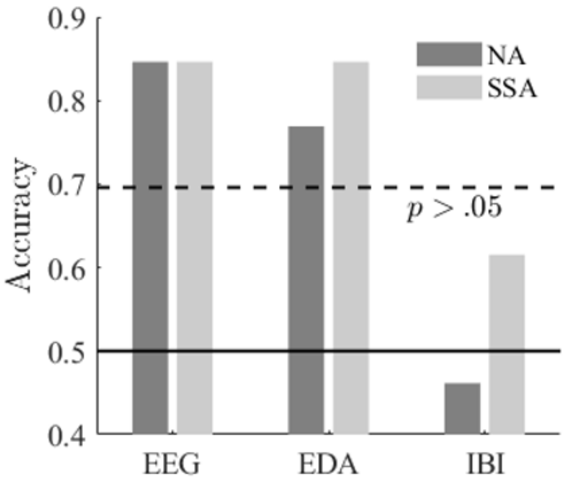

Fig. 2. Classification accuracy of inferring attentional group from ISC in EEG, EDA and IBI where each participant was designated to be in the attentional group for which he or she they showed the highest ISC. Data are presented seperately for narrative-attending participants (NA) and short-stimuli attending participants (SSA). Theoretical chance level is 0.5. Statistical chance level is indicated by the dashed line.

IV. DISCUSSION

We showed that PS in both EEG and EDA is indicative of shared attention: EEG and EDA signals of participants are more strongly synchronized with those of participants in the same attentional condition compared to the other. For IBI, we did not find this.

In our setting, all participants attended to the auditory stimulus. While participants in the short-stimuli condition were instructed to ignore the narrative, it was probably hard to do this at times without concurrent short-stimuli. In contrast to e.g. the study by [9], our participants did not have another task at these times and their attention was likely directed to the auditory environment, since they expected an auditory stimulus that was relevant for them. We therefore expect that the difference between the groups and therefore, our PS effects, will be strongest when only considering the times during which concurrent short-stimuli are played. In future analysis we will first recover occurrence of generally high PS (which will also indicate which events generated generally high shared attention) and then focus analysis at those times, to examine whether this will result in even clearer effects, perhaps also showing an effect for IBI.

EEG PS performed relatively well, as might have been expected based on previous PS literature and the more direct link with attention. However, EDA did well too, which, even though wearable EEG systems are available, is convenient from a user perspective. The finding that IBI performed worst may not be unexpected given the fact that the relation between heart rate and mental state seems less straightforward than EDA. Whereas EDA has consistently been found to be positively related to arousal [20], the relation between emotional stimuli and heart rate has been found to be more complex. Both positive (e.g. [13]) and negative (e.g. [21]) relations between heart rate and arousal been reported. The reason for this is probably that arousal can be associated with the body being prepared for action, cf. the defense reflex, or with a concentrated, focused state, cf. the orienting reflex, where the defense system is associated with heart rate accelerations and the orienting system with decelerations [22]. The type of response to a certain emotional stimulus can differ between individuals and occasions.

In future analysis, we will examine patterns of synchrony in the different modalities as a function of stimulus type. Events relevant for mental tasks (counting the beeps) may be strongly associated to synchrony in EEG, whereas emotional stimuli (IADS and the instruction to sing a song) may be strongly associated to synchrony in EDA. Patterns of multimodal synchrony might even allow us to identify the type of shared mental activity and therewith the instigator of shared attention. Combining synchrony measures from different modalities may support detection of (certain) relevant events, although it is still unclear how this can be done best [23]. It is also of interest to relate PS to behavioral or cognitive performance on tasks related to the to be attended stimuli. An individual's (moment of) low PS may be predictive of later poor performance. Finally, we want to mention that in the current study, we purposely examined interpersonal PS in a situation with very limited eye- or body movements, and no interpersonal communication. This was done in order to avoid possible confounds of physiological measures with movements [24] and with the view of studying PS in the context of attention, apart from interpersonal interaction. However, it would be of interest to bring this view together with the large literature on interpersonal synchrony in behavioral measures such as gestures and speech during social interaction [25].

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