

Does Machine-Mediated Interaction Induce Inter-Brain Synchrony? - A Hyperscanning Study

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Abstract—We present a study in which participants were trained in several sessions to control a (comparatively simple) robot via an EEG-/motor imagery-based Brain-Computer Interface (BCI). In the final (experiment) session pairs of participants were formed and each participant controlled one of two robots in a shared space. EEG data was recorded synchronously from both participants. We performed a joint data analysis on the datasets and found increases of phase-locking in μ - and θ -band. One such phase-locking effect appears to be time-locked to the start of the robotic action.

I. INTRODUCTION

Human interaction involves complex alignment and communication processes, even in pretty simple social situations. The neural foundations of these processes are barely understood. Schillbach et al. even refer to them as the "dark matter of social neuroscience" [17]. They have become one of the most active fields of research in cognitive neuroscience. One central technique in that regard is the synchronized recording of neural activity from more than one participant, called hyperscanning.

Recordings of single participants involved in social interaction have been performed for quite some years now and have yielded some remarkable results. However, hyperscanning allows for the joint analysis of human brain activities. Simply put, hyperscanning allows to monitor all brains involved in social interaction - and their interplay. It, thus, allows for a whole new access to this "dark matter".

Most hyperscanning studies use EEG recordings [3], [2], [4], [6], [12], [10] not only because it is the most cost efficient among the established neural imaging techniques, but also because it outperforms most other recording techniques in terms of temporal resolution. A high temporal resolution is advantageous in this research field, as most interaction-shaping processes take place in real-time in the range of seconds.

Various studies reported correlations in hyperscanning data of interacting participants. Analytic measures used in that regard include Coherence Analysis, Granger Causality [2] and Phase-Locking Analysis [6], [13]. The fact that several studies were able to demonstrate an alignment in the phases of EEG signals is particularly remarkable. Even such fast changing features as the phases of neural signals are temporarily aligned when humans interact.

Scenarios in which human interaction has been studied using hyperscanning are many-fold: Astolfi et al analyzed neural data recorded from pilots during flight simulations [1].

Babiloni et al. performed hyperscanning on participants involved in a card game [4]. Several hyperscanning studies established a leader/follower relationship between participants performing motor-tasks: Yun et al used a common/everyday motor task (finger pointing) [18] and Holper et al a rhythmic motor task (finger tapping) [9]. Sanger et al extended this to a more complex motor skill (guitar playing) [16].

Another active research field of cognitive neuroscience are Brain-Computer Interfaces (BCIs) which derive commands for computer systems from neural activity in real-time. Although BCIs have been applied to control robots before [5], [8] - even with multiple users [7] - to our knowledge there has not yet been a joint analysis of hyperscanning data in such a setting. This might, however, be a promising field of study, as machine- and even robot-mediation of human-human interaction becomes increasingly important - and common - in our societies. Furthermore it allows for remote settings which are impossible without machine-mediation (e.g. video conference or telepresence systems).

We present such a hyperscanning study involving machine-mediated interaction, i.e. BCI control of robots in a shared space.

II. METHODS

This study aims to evaluate whether the neural alignment effects described in the introduction also occur when interaction is machine-mediated. If so, hyperscanning studies in such settings would constitute a whole new research branch to explore. The present study is therefore intended to be pilot study, laying foundations for future studies with more elaborate collaborative interaction tasks. For now the scenario is, however, kept quite simple on purpose:

Two participants were placed face-to-face on two sides of a desk. Two small cube-shaped robots called TAOs [15] were placed onto the desk. These robots had to be steered to the left/right side of the desk using motor imagery of the left/right hand (see figure 1). The study consisted of 150 trials. In each trial 1. both participants received auditory cues indicating their next task (drive left/right or pause); 2. a countdown occurred; 3. participants started their motor imagery and 4. the TAOs started moving accordingly.

A. Experimental Procedure

In each trial each participant received a cue via headphones to either steer their TAO to the left/right side of the desk (for her/his perspective) or to just watch the partners performance (pause). In the last case BCI control was switched off for that participant. Each participant received

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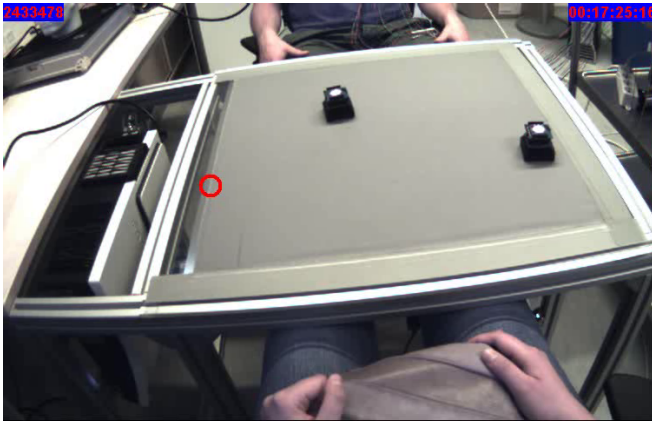


Fig. 1. Scene camera of one participant

the cue 'left'/'right' in 62 or 63 trials respectively and the cue 'pause' in 25 trials. Participants were unaware of their partners cues.

After both participants received their cue, a (common) countdown (3 to 0) was projected onto the desk, after which the participants started imagining their hand movements. After one second there was enough data for the classifier to infer participants intentions a first time and the TAOs started to move accordingly. The classification was repeated every 0.5 sec. on all data that had accumulated since the countdown's expiration. Hence, the TAO could potentially change direction every half a second. When the classification output did not reach a certain threshold the TAO responded by stopping. 5.5 sec. after the countdown's expiration the trial ended and both TAOs returned to their origins automatically.

Three conditions emerged from the cues given: Cue congruent condition (50 trials), in which one participants had to steer her/his TAO to the right and one to the left desk side (both TAOs headed towards the same side of the desk). Cue incongruent condition (50 trials), in which both participants had to steer their TAO to the individual right or left side (both TAOs headed for different sides of the desk). And solo condition (50 trials), in which only one participant performed motor imagery. All participant pairs were presented with the same randomized sequence of conditions.

B. Apparatus

For data recording we used two 16 channel EEG devices (GTec GUSBamp) with Ag/AgCl-electrodes fixed to Easy-Cap EEG electrode placement caps. Electrode positions were Fz, Cz, Pz, Oz, F4 C4, C6, CP4, P4, PO8, F3, C3, C5, CP3, P3 and PO7. Impedance was kept below $10k\Omega$. Participants were trained individually in at least 4 sessions on different days until they achieved reasonable control over the TAO. All eight participants achieved at least 70% accuracy during the training.

Online classification was performed using a chain of FFT-based frequency filtering, Common Spatial Pattern Analysis for feature extraction and Fisher Discriminant Analysis for the final classification.

During the experiment, participants were equipped with an additional eye tracking system. However, the eye-tracking data is not part of the present analysis.

C. Data Analysis

An Independent Component Analysis (ICA) was performed on the data. Components containing ocular artifacts were identified visually and removed from the data. All subsequent analysis was done on segmented data (one segment per trial). Segments reach from 3 sec. before to 3 sec. after the countdown expired. Segments were visually inspected after ICA pruning and those with heavy residual artifact contamination were rejected. One to three trials were rejected per dataset.

For within-participant analysis, we performed a cross-validations on training and experiment data. Furthermore, we visualized magnitudes of Event-Related Desynchronizations (ERDs) [14], which are the neural activity pattern the participants are supposed to evoke using motor imagery.

For cross-participant analysis we used the Phase-Locking Value and Statistics (PLV/PLS) [11]. For a given signal (e.g. an EEG signal) the phase of the signal can be approximated for a given frequency and time, by well established mathematical methods (e.g. using Wavelet Transformation). Phase-locking describes the effect, that the difference in phase between two signals is similar over iterations [11]. Here PLV is computed between the signals from corresponding electrodes of both participants (e.g. C3 of participant 1 with C3 of participant 2). For each frequency point, trial and time point the phase difference ϕ_δ between the signals is computed¹. ϕ_δ is expressed as a complex number. The average of the ϕ_δ over trials is computed. The PLV is defined as the norm of this average and lies in the $[0, 1]$ interval. The PLV is close to one when all ϕ_δ face a similar direction. It is close to zero, when the ϕ_δ are equally distributed and cancel one another out during averaging.

The PLS aim to define statistical significance of PLVs. Trials of one participant are shuffled randomly before computing the PLV, resulting in a shuffle-based PLV_s . As signals of different trials are now combined it can be assumed that there is no phase-locking between those datasets. This is repeated 200 times and the fraction of shuffled PLV_s that are smaller than the original PLV is called Phase-Locking Statistics PLS. If this exceeds 0.95 (hence, at most 5% of the PLV_s are larger than the PLV) this is considered significant phase-locking.

As PLS values are computed for more than thousand samples ($256 \frac{\text{samples}}{s} \cdot 6 \text{ s} = 1536 \text{ samples}$) the PLS value can be expected to reach the threshold of 0.95 by chance several times during an analysis. To overcome such occurrences of spurious significances, we performed a 10 sample temporal smoothing on the PLS values.

We want to establish a criterion for long-lasting/stable phase-lockings for this study. However, the characteristics of high-frequency signals generally change faster than those of

¹Using a Wavelet Transformation with a complex Morlet Wavelet

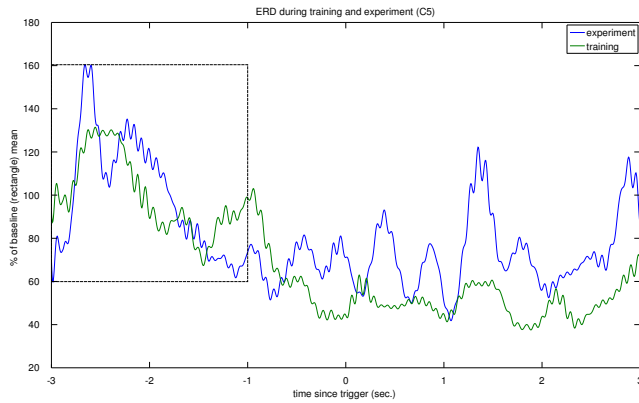


Fig. 2. Exemplary magnitude visualization of ERDs for training and experiment of one participant. The drop that occurs around the 0 *sec.* is less clear for experiment data.

low-frequency signals. Hence, the definition of stable phase-locking should be dependent on the signals frequency. We define a portion within the smoothed PLS timer series which is continuously > 0.95 for at least half a period of the center frequency of the filter band to contain stable phase-locking. For example, the θ band ($4 - 7Hz$) has a center frequency of $5.5Hz$. Thus, we consider any portion with a PLS value > 0.95 for more than $0.5 \cdot \frac{1}{5.5Hz} \approx 90.9 ms$ to contain stable phase-locking.

III. RESULTS

The first result was that - although, participants had stable control over the system during (individual) training² - classification accuracy dropped to $\approx 50\%$ (chance) during the experiment session.

A five bin cross-validation on the experiment data yielded good discriminability ($\approx 75\%$). Performing a common cross-validation on training and experiment data revealed poor results. Hence, data characteristics must have change between training and experiment. Visualization of the ERDs [14] (the "target" brain activity pattern) left us with the impression that ERDs were less pronounced during the experiment compared to the training sessions. This is depicted for electrode C5 in figure 2. A possible explanation for this effect could be that the presence of the partner made participants excited and disturbed their concentration.

Phase-locking analysis was done including all trials of an experiment that were not rejected during visual inspection. Additionally, we split these trials into three disjunct groups and performed the same analysis on each group separately. The three groups were: solo trials, movement congruent trials and movement incongruent trials.

All trials in which only one participant acted (and the other watched) were assigned to the solo trials group (50 trials). The remaining 100 trials were distribute between two groups based on the actual TAO movement (and thus on the classifier output): During a trial a series of 11 commands

²Even during a brief retraining which took place directly before the experiment.

were sent from the BCI system to the each TAO in 0.5 *sec.* intervals (see II-A). If after executing these 11 commands (supposing the TAOs had ideal driving behavior) both TAOs were located on the same half of the desk, the trial was assigned to the movement congruent group. If both TAOs would end up on different halves of the desk, the trial was assigned to the movement incongruent group.

For one pair 95 of 100 trials were movement congruent. Hence, PLS could not be computed reasonably after splitting into movement congruent and incongruent trials. For this pair phase-locking analysis was conducted only once including all trials and once including solo trials.

For further phase-locking analysis, trials could be grouped according to cue congruent and cue incongruent conditions (see II-A). However, as the participants did not know the cue of their partner, their only way to infer this cue was the movement of the partner's TAO. As these were independent from the given cues for all but one participants, grouping trials according to cue conditions is infeasible.

For all pairs significant phase-locking was found in μ band ($8 - 13Hz$) and θ band ($4 - 7Hz$). We will consider these findings systematically regarding their spatial and temporal distribution and distribution between groups of trials (movement congruent, movement incongruent and solo trials).

Analyzing the spatial distribution of phase-locking including all trials, we found phase-locking in θ -band was localized mostly around the C3 and C6 electrodes, with some bias towards the left hemisphere including CP3 and P3. Phase-locking was found less frequently in frontal regions and at the central electrodes (Fz to Oz). For μ -band phase-locking was found in both hemispheres almost equally. It also occurs at central electrodes (Cz to Oz) but less frequently in frontal regions. The spatial distribution of stable phase-locking for all four participant pairs is depicted in figure 3.

When splitting trials by TAO movement, one common result was that for solo trials very few phase-locking could be observed in θ -band. In μ -band, on the other hand, quite some phase-locking could be observed for solo trials, with a comparable spatial distribution as reported above. The distribution of phase-locking between movement congruent and movement incongruent trials was mostly inconsistent among pairs and electrodes.

Phase-locking was rarely observed before the countdown reached 0. Any such phase-lockings had short durations and occurred inconsistently.

Finally, one phase-locking effect could be observed in θ -band which occurs with quite some spatial and temporal consistency. This phase-locking appears in the area of electrodes C5, C3 and CP3 at about 1.2 *sec.* after the countdown expired (0.2 *sec.* after the TAOs started moving). Figure 4 shows the PLS and PLV time course at electrode C5 computed on all trials for all four pairs. For three pairs this reaches significance, for the fourth pair the PLS and PLV values still show a clear peak. When analyzing groups of trials separately, this phase-locking mainly occurred in movement incongruent trials for two of the pairs, while for the third pair it mainly occurred in movement congruent

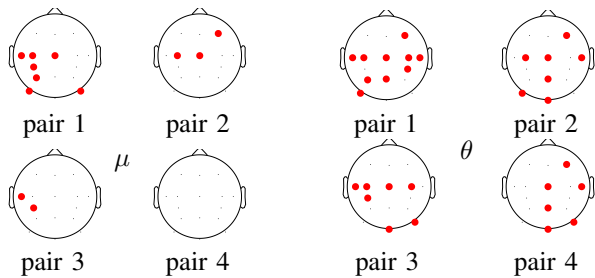


Fig. 3. Spatial distribution of stable phase-locking for all four pairs in θ and μ band.

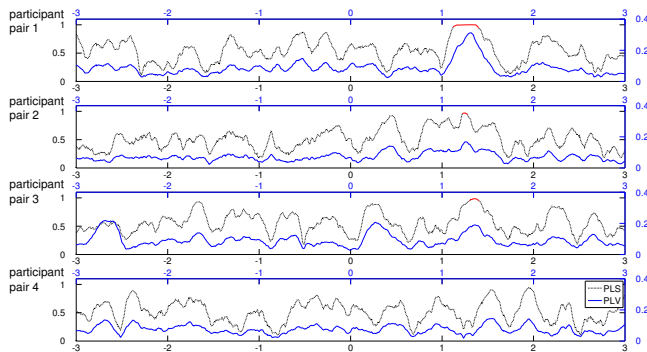


Fig. 4. PLS and PLV for all pairs computed on all trials at location C5. The PLS curve is plotted in red, when it exceeds 0.95. At 1.2 sec. phase-locking was significant for three out of four pairs.

trials.³ The right hemisphere showed a similar behavior, however, peaks in PLV and PLS were smaller and PLS reached significance only occasionally.

IV. CONCLUSION

The task given involved only limited interaction. Participants were simply placed in a face-to-face setting and controlled distinct robots in a shared space. This, compared to other studies, rather shallow interaction still yielded significant phase-locking. However this phase-locking vanished in θ band when only one participant actually acted.

For future experiments, the fact that data characteristics (i.e. ERDs) might change in the experiment compared to the training is to be considered. One consequence could be to perform training in pairs, aiming to make training- and experiment-environment more alike.

Considering the difficulties involved when performing EEG measurements in natural human-human interaction and the growing importance of remote and machine-mediated human-human interaction, we consider the machine-mediation of such interaction settings to be a relevant (and still quite neglected) field of research. The results of this study support our notion that robotic actions in a shared space can be a viable way to implement such machine-mediation of human-human interaction.

³For one pair phase-locking was not analyzed for movement congruent and incongruent trials separately, see above.

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