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SSVEP-BASED COVERT COMMUNICATION USING HYPERSCANNING

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ABSTRACT: Communication by means of evoked brain signals is one of the main applications of brain-computer interfaces (BCIs). Commonly, in BCI applications the user's intention is directly fed back and openly perceivable. Here we used hyperscanning to investigate a communication approach, in which two users can covertly communicate by brain signal modulation. To achieve this, we artificially generated synchronous and asynchronous oscillatory brain activity by presenting a choice of two flickering stimuli inducing steady-state visual evoked potentials (SSVEPs) and provided feedback that indicated the synchronicity of the brain signals of participant pairs. We used different approaches to determine synchronicity. When we used broadband activity, the accuracy varied considerably between participant pairs, which could be attributed to individual differences in the timing and the amplitudes of SSVEPs. However, when we involved features reflecting the stimulus frequencies, the predictions were highly reliable. Beyond demonstrating the feasibility of our approach, our findings have the potential to identify challenges in studying social interaction using hyperscanning.

INTRODUCTION

Hyperscanning refers to recording brain data from more than one person simultaneously. It is increasingly being used to investigate neuronal correlations during social interaction [1,2] and learning [3]. A common approach in hyperscanning is to determine the degree of brain-to-brain synchrony, i.e., the synchronicity, of two users. Portable electroencephalography (EEG) headsets allow involvement of multiple individuals in real-world environments, e.g., a classroom [4]. Simultaneous EEG recordings from multiple users have also been utilized in brain-computer interface (BCI) research to incorporate collaborative/competitive BCI control in video games [5] and to increase the decoding accuracy in single trial classification of visual evoked potentials (VEPs) [6]. Collaborative BCIs have the potential to increase the signal-to-noise ratio by combining activity from multiple brains. For communication purposes, collaborative control would not have a practical benefit, since users would be required to know their mutual intention. In contrast, a brain-to-brain communication, in which one user sends a message and the other user infers the message from comparing BCI-generated feedback and their own intention, could enable a covert communication only perceivable by the users involved.

Brain-to-brain interface control using brain stimulation techniques applied to the receiver has been demonstrated in rats [7] and humans [8,9]. Here we introduce a noninvasive approach for implementing indirect brain-to-brain communication by simultaneously recording EEG signals from both the sender and the receiver of a communication. The content of the communicated message is inferred from feedback indicating the degree of brain synchrony. We artificially induce brain synchronicity and asynchronicity by presenting flicker stimuli. While the approach of decoding the steady-state visually evoked potentials (SSVEPs) induced by these types of stimuli is a common approach for controlling BCIs [10,11], decoding the synchronicity of brain signals from two brains induced by flicker stimuli has not yet been performed.

MATERIALS AND METHODS

Subjects and Task: Fourteen participants (mean age 26.4±4.2 years, 8 male) were recruited to participate in the hyperscanning BCI experiment, resulting in seven participant pairs, or dyads (6 male/female, 1 male /male). They provided informed consent and received 25 € for participation. The study was approved by the Ethics Committee of the Otto von Guericke University, Magdeburg, Germany.

Two participants were seated next to each other, each in front of a custom stimulation device, which consisted of

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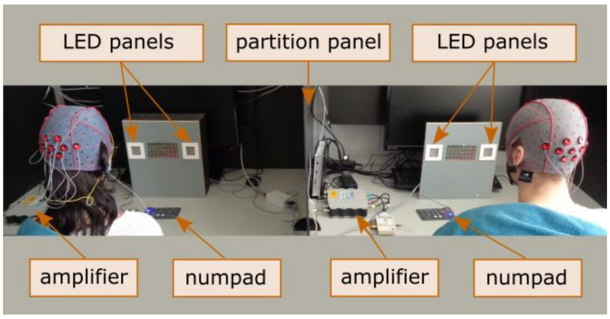

Figure 1: Technical setup for the hyperscanning BCI.

two small light-emitting diode (LED) panels (35×35 mm²), 18cm apart. A partition panel on the desk prevented the participants from being distracted by the stimuli presented to the partner (see Fig. 1 for the technical setup). The task of the participants was to silently communicate yes/no responses by focusing on particular flickering stimuli. One participant was asked to send a yes/no response (Sender role) and the other was asked to infer the response from the feedback generated by the BCI (Receiver role). The roles were changed between participants halfway through the experiment. The experimenter provided verbal instructions to guide the participants throughout the experiment. A trial started by verbally cueing the participants to focus on their next intended response. Subsequently, the presentation of the stimuli started. The left LED panel flickered with a frequency of 9.09 Hz (110 ms stimulus onset asynchrony) and was associated with the response “yes”. The right LED panel flickered with a frequency of 11.11 Hz (90 ms stimulus onset asynchrony) and was associated with the response “no”. We identified these flicker frequencies as reliable following pilot testing with individual test subjects using 9.09 Hz, 11.11 Hz, 12.5 Hz and 15.0 Hz stimuli.

The occipital brain oscillatory activity of the participant classically synchronizes with the flicker frequency of the panel on which the participant focuses their gaze, forming the basis of a classical SSVEP-based BCI. The stimuli for the two participants were synchronized, i.e., the LEDs in front of them were on and off at the same time. After five seconds, the stimulus stopped and the synchronicity feedback was presented by a computer voice saying “equal” if the BCI detected synchrony between the EEG signals of the participant pair, and “different”, if the BCI detected asynchronous EEG signals. Afterwards, the Receiver combined their own internal response with the synchronicity feedback, inferring what the Sender had intended to answer and pressed the corresponding button on a keypad. The inferred Sender response was presented as inference feedback (“yes” or “no”). Finally, the Sender assessed whether the inferred response was correct or not by pressing the corresponding button on a keypad, yielding a third feedback item, which could be “correct” or “wrong”. This final feedback provided the Receiver with the ground truth. Note that for silent communication only, the synchronicity feedback is required but no button press. The button presses and the additional feedback were only necessary for evaluation purposes.

A session started with 20 training trials in which all combinations of responses were cued an equal number of times (yes/yes, no/no, yes/no, no/yes) and no feedback was presented. These trials were for initial classifier training. Afterwards, the feedback mode started, and the experimenter asked subjective questions, e.g. “Do you play an instrument?”. After each trial, the participant’s intentions were determined from their responses and the classifier was retrained. We also performed trials in which the participants were asked to communicate one of 32 items. A table was presented, showing 32 numbers and letters, or 32 cards of a card deck. Each item shown in the tables was assigned a binary color code, where five bits were coded with green and red bars located under each item. The participants associated green bits with “yes” and red bits with “no”. This approach required five trials, with the concomitant five binary decisions, to communicate one item. Trials in which participants made mistakes according to their own statement (e.g., wrong button press) were immediately excluded by the experimenter from the further analysis. Therefore, the number of questions asked varied, resulting in a total number of 118.7±6.5 trials on average, including training trials.

Recordings: EEG data were recorded with a sampling frequency of 512 Hz from ten electrode sites (OI1h, OI2h, PO7, O1, Oz, O2, PO8, POO1, POO2, Fz) and referenced against the right ear lobe using two g.tec gUSBamp devices. Synchronization of EEG recordings was achieved by sending a trigger signal simultaneously to both amplifiers and correcting for time shifts in the received data buffers during online processing. The 5 s data segments were notch filtered to remove 50 Hz line noise and bandpass filtered between 5 and 30 Hz. Finally, we resampled the data to 256 Hz sampling rate to reduce computational demands in further processing.

Decoding approach: Different decoding approaches were applied in the online and offline analyses described in this section. All approaches used canonical correlation analysis (CCA), a statistical method that maximizes correlation between two variable sets X and Y:

$$(U, V) = \underset{A,B}{\operatorname{argmax}} \operatorname{corr}(XA, YB) \tag{1}$$

where the canonical coefficients in A and B linearly combine X and Y, such that the correlation is maximal in the first variables of matrices $U = XA$ and $V = YB$, and decreases with increasing component ranking. The approach suggested by Lin et al. [12] has become established in BCIs as a reliable way of detecting SSVEPs and uses X as the time varying brain signals (EEG) and Y as a set of sine and cosine functions with frequencies equal to the stimulus frequencies and their harmonics. We used this approach to determine classifier features, using the two stimulation frequencies, 9.09 and 11.11 Hz, and their first harmonics, resulting in four features per stimulation frequency. We used only the first two canonical correlation coefficients per stimulation frequency and participant as features, resulting in four

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features per participant and eight features per dyad. We refer to this feature set as R_{SSVEP}. This feature set specifically captures the brain activity associated with the flicker stimuli. To investigate whether the brain synchronicity, which we artificially induced through the stimulus, can also be predicted when we do not include information about the stimulus, we calculated another feature set by setting X as the EEG signal of one participant and Y as the EEG signal of the other participant. With this approach, we investigated whether we can determine synchronous brain signals from broadband (here limited to 5-30 Hz) brain activity. Here we used only the first two canonical correlation coefficients and refer to this feature space as R_B and to the canonical components as U_B and V_B, respectively.

During online decoding, we used the R_{SSVEP} feature set and trained a k-nearest-neighbor classifier (kNN) using trials with equal stimulation frequencies as one class and trials with different stimulation frequencies as the other class to decode the synchronicity and present feedback accordingly. We also predicted the synchronicity directly from this feature set in a leave-one-out cross-validation (LOOCV) using a nonlinear support vector machine (SVM) classifier and radial basis function (RBF) as kernel. Finally, the R_{SSVEP} feature set was used to classify the SSVEP response in single participants as in conventional SSVEP-based BCIs, using LOOCV and the RBF SVM classifier. To test whether the direct classification of synchronicity is advantageous compared to classifying the SSVEP of the participants separately and subsequently determining the synchronicity indirectly by comparing the predictions of both participants, we calculated the indirect decoding accuracy from the predictions obtained by conventional SSVEP decoding.

In a final approach, we used LOOCV and RBF SVM to decode the synchronicity of brain activity based on broadband EEG signals, using the R_B feature set as described above. To compensate for potential shifts in individual latencies of VEPs, we shifted the signals in steps of single sample points against each other before applying CCA and compared the maximum accuracy of the time-shifted analysis with the accuracy achieved with the non-shifted signals.

We performed permutation testing for all reported classification approaches by permuting the labels that indicate the focused stimulus frequency and repeating the LOOCV 1000 times. This procedure resulted in a distribution of chance accuracies from which we determined the mean chance level and the 95% confidence intervals.

RESULTS

The intention of participants with Sender role was correctly determined on the basis of the feedback regarding the synchronicity of their brain activity with that of the Receiver in μ=93.6% (σ=10.7%) on average during the BCI hyperscanning. The LOOCV using the same approach (direct classification of synchronicity) yielded an average accuracy of μ=94.3% (σ=9.4%), which was not statistically significantly different to that attained using online decoding. Using the approach of indirectly classifying synchronicity resulted in an average accuracy of μ=94.7% (σ=9.2%) and was neither different from online decoding nor from direct classification of synchronicity. Conventional decoding of the stimulus frequency from SSVEPs using R_{SSVEP} features resulted in an average decoding accuracy of μ=97.4% (σ=6.8%) across all 14 participants. These decoding accuracies are shown in Fig. 2 for each participant pairs. It can be seen that the classification of synchronicity is bounded by the accuracy in detection of the focused stimulus frequency of the less well-performing participant.

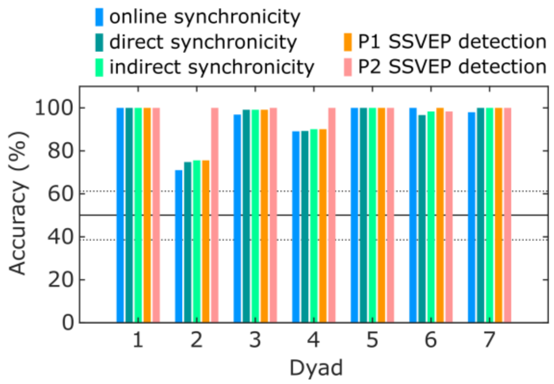

Figure 2: Decoding accuracies achieved with different decoding approaches using the R_{SSVEP} feature space. All bars show accuracies obtained with LOOCV except the blue bar, which shows online accuracy. Solid and dashed black lines indicate the mean and upper 95% confidence interval of the chance level obtained by permutation testing.

In a next step, we did not include information about the stimulus frequencies but rather calculated canonical correlation coefficients using the broadband signals from all channels of both participants as variable sets to use them as features for classification of the brains' synchronicity. This analysis showed strong variability between dyads, ranging from 50.5% to 97.2% decoding accuracy (μ=72.5% σ=18.1%). The decoding accuracy could be improved by shifting the time series of either participant to compensate for potential individual differences in visual processing latencies. Selecting the maximum accuracy from the latency shifts, decoding accuracy ranged from 62.2% to 97.2% (μ=78.2% σ=14.5%). Latency shifts resulting in these improved accuracies ranged from 0ms to 23.4 ms (μ=10.0 ms, σ=9.0 ms).

To investigate the reason for the large inter-dyad differences when using the R_B features, we calculated the spectra of the first component in U_B, obtained by CCA, of each trial and participant and averaged across trials where the visual stimuli were identical in both participants. For each stimulus frequency and their first harmonics, we calculated the Pearson correlation coefficient ρ between amplitudes (obtained by the spectra of the first component in U_B) and decoding accuracies

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(achieved with the broadband synchronicity classification approach) across dyads (see Fig. 3). We found a significant correlation ($p<0.05$) for frequencies 9.09 Hz ($\rho=0.93$), 11.11 Hz ($\rho=0.86$) and 18.18 Hz ($\rho=0.73$) but not for 22.22 Hz ($\sigma=0.34$). Therefore, the accuracy of broadband synchronicity classification is influenced by the magnitude of SSVEP amplitudes.

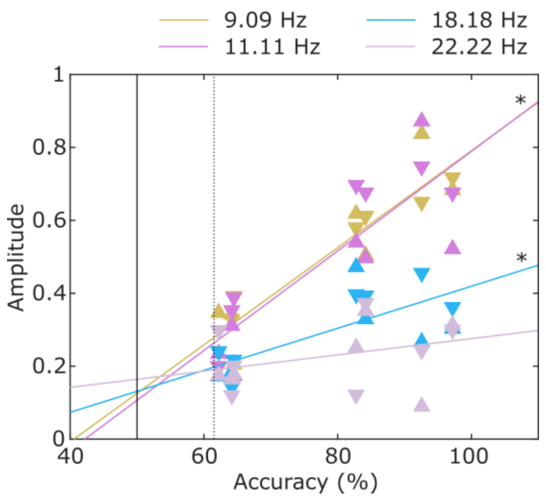

Figure 3: Decoding accuracies of broadband synchronicity classification according to signal amplitudes at different stimulus frequencies and their 1st harmonics. Regression lines visualize the correlation, asterisks indicate significant correlation ($p<0.05$). Upward and downward triangles indicate first and second participant of a dyad. Solid and dashed black lines indicate mean and upper 95% confidence interval of the chance level obtained by permutation testing.

DISCUSSION

The study demonstrates that covert communication can be performed using a noninvasive hyperscanning BCI. We induced synchrony of brain signals by presenting synchronous and asynchronous visual stimuli and used the degree of synchrony as a feedback signal. Brain-to-brain synchrony was decoded with an accuracy close to 100% in five dyads. This was only constrained by the lowest single subject SSVEP detection accuracy within a dyad in two instances using features that incorporate prior knowledge about the flicker frequency of the stimuli. Although direct classification could potentially exploit multivariate relationships between individual R_{SSVEP} features, decoding accuracy was not significantly different from the indirect approach that compared independently predicted SSVEPs of each participant. Thus, both approaches are well suited to implementing the proposed BCI for covert communication.

A secondary aim of the study was to investigate the feasibility of classifying brain-to-brain synchrony in general, without taking knowledge about stimulus frequencies into account. When we used broadband activity to calculate CCA features, decoding accuracy strongly depended on the SSVEP amplitudes, i.e., on how much the stimulus was reflected in the brain signals. Two of the dyads were highly reliably decoded (>90%), two were moderately reliably decoded (>80%) and three achieved accuracies slightly above chance level (>61.5%).

Flicker frequencies in the alpha band have been shown to have an impact on attentional processing, which is presumed to result from interactions between the flicker rhythm and the endogenous alpha rhythm [13]. Note that although the stimulus frequencies we used both lie within the alpha band, common CCA-based decoding resulted in high accuracy. The interaction between flicker stimuli and the endogenous alpha rhythm is, however, highly variable, with dependency on the individual alpha frequency and also the particular source of the endogenous alpha rhythm [14]. Future work should include exploration of potential relationships between synchronicity decoding accuracies and both individual alpha activity and flicker frequencies within and outside the alpha band.

Our approach provides an alternative strategy for hyperscanning experiments, given the general discussion on interpretability of coherence measures applied for investigating social interaction with this technique [15,16]. Mainly, however, our findings uncover important challenges in hyperscanning, namely that individual differences in EEG signals can lead to quite different degrees of brain-to-brain synchrony detection. This variability is illustrated by our findings when we classified synchronicity using R_{SSVEP} and R_B features. The SSVEP amplitude was sufficiently high to enable decoding of the focused frequency at close to 100% in 12 of 14 subjects, and the synchrony decoding based on these features was related to these accuracies. However, the SSVEPs were not sufficiently represented in the EEGs of some dyads to enable comparably reliable synchrony decoding from broadband activity. Furthermore, latency shifts of evoked potentials might be a limiting factor for determining brain-to-brain synchrony, as not only suggested by our analyses but also known from the literature.

In future work, features based on coherence and information theory could be investigated for suitability of synchronicity detection for comparison with our broadband CCA approach. A limitation of our approach to performing covert communication is that it can only be performed in binary mode, by inferring binary responses from feedback indicating the degree of synchrony. However, using color-coded items, the participants also could communicate letters in five steps of binary decisions and thus, the proposed BCI could potentially be used to communicate whole sentences. Another limitation is that SSVEPs depend on eye movements, and only sensory processing is decoded rather than higher cognitive functions. However, gaze-independent paradigms communicating binary decisions using attention processes exist [17], which would be suitable for decoding brain-to-brain synchrony as well, and might be the next step towards a gaze-independent, covert communication BCI.

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CONCLUSION

SSVEPs can be used to stimulate brain-to-brain synchrony, which was decoded with high accuracy using stimulus-based features and enabled dyads of participants to reliably communicate binary messages, not perceivable by external observers. Synchrony features obtained from broadband signals reflected the synchronous stimulating signals, resulting in reliable decoding only in some dyads. These findings may have implications for other neuroscientific hyperscanning studies investigating social interaction.

DATA AVAILABILITY

The datasets used for this study are available to download from https://zenodo.org/doi/10.5281/zenodo.10809098.

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