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**Faculty of Electrical Engineering,
Mathematics & Computer Science**

Finding Neural Correlates for Social Relationships using EEG Hyperscanning

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Abstract

Brain-computer Interfaces are a growing field of Human-computer Interaction that is gaining importance with sensors becoming cheaper and more accessible. This paves the way to these devices being used in daily life. A possible field of application is affective computing, in which the computer attempts to be environmentally aware of the human aspects of the user, such as emotions and the social context. This project explores the ability for BCI (in this case EEG hyperscanning) to be used to detect the social context, by attempting to find neural correlations for social relationships between two users in a joint-attention setting. The experiment consists of two users who can belong to either of two dyad classes ("strangers" or "lovers") getting exposed to a series of visual stimuli while their brain-activity is being recorded (EEG recording using 2 BioSemi Active2). The metric that is investigated primarily is the Inter-brain weighted phase lag index (WPLI) as defined by [Vinck et al., 2011]. The results of this experiment, based on a user test with 6 dyads, show a weak significant difference (.8 CI) between the dyad groups in the alpha and theta frequency range. The conclusions drawn are that there are clear indications for the WPLI being a usable metric for detection of social relationships, however the joint-attention task used in this experiment is a rather passive form of interaction, while other experiments with more active tasks seemed to cause stronger differences in the signals. This might hint at the effect primarily stemming from active interaction.

Contents

List of Figures

List of Tables

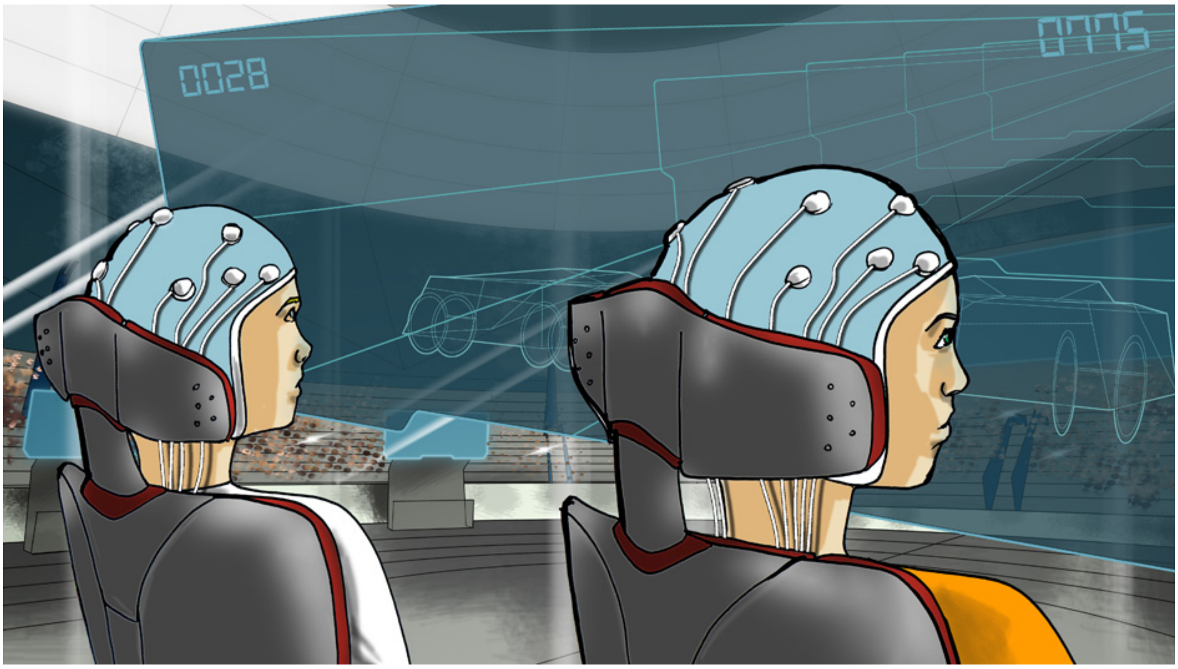


Figure 1: artist impression of Parathletes competing in a Cybathlon using Brain-computer interfaces goo.gl/nWyD1N

1 Introduction

Brain-Computer Interfaces (BCI) are a growing field in Human-Computer interaction and are widely researched as a potential new method of user-interaction with computers. They are widely regarded as a potential additional interface to extend the possibilities of mouse, keyboard and touchscreen, adding another dimension that does not rely on first translating thoughts to motor output that then manipulates a Human-device Interface whose input is then translated to digital data. This path of translating through different domains could potentially be shortened by having direct brain-computer interaction. One of the primary applications for BCI, outside of the medical field, is gaming. Controlling a game-character by brain activity potentially increases immersion into the game world and thus gives the user a more intense perception of the game. [Friedman, 2017] showed that users perceive an embodiment of their game-character when controlling a VR based game using a BCI [Gu et al., 2016]. Opposing these explicit forms of interaction using BCI, there is also a trend of researching the more implicit forms of interaction through a BCI, the so-called passive BCI, which are based around sensing the users mental state without the user attempting to modulate his input to control a system. These passive BCI can for example detect the users mood, emotions, relaxation, concentration levels or mental workload in order to match the system to the users state of mind, for example in affective computing, adaptive automation, or to improve the workings of systems that primarily work with explicit interaction (such as [Dal Seno et al., 2010] P3 speller, which incorporates passive detection of error potentials in order to improve the classification).

The paradigm of controlling a computer or other technical device directly, using a brain computer interface is, however, just one aspect of the field. In affective computing the computer already attempts to detect the users mood or emotional state (possibly based on BCI data, but also other measures[1]), the next step for computers to sense its surroundings is to also being able to detect and react to the social relation between the people in the room. Among others, [Schilbach et al., 2013b] proposed that neuroscience needs to be extended towards a "second person neuroscience" in order to close that gap. The technique to do so is called hyperscanning and describes the use of multiple BCI devices monitoring one brain each and then investigating the interaction (and social relation) by studying how the activities in both brains correlate.

This paper provides an overview of the current state-of-the-art in BCI (Section 2) with a focus on EEG based emotion detection (Section 2.3.1) and on the investigation of social relations using EEG hyperscanning (Section 2.4). It ends in a proposition for Future Research (Section 3) and proposes a Methodology for such research (Section 4). As the focus of this paper lies on emotion detection and hyperscanning, the level of detail, especially with regards to the technical implementation is higher in these section than the rest of the paper.

2 Brain-Computer Interfaces

Brain-computer interfaces are communications systems in which messages or commands from an individual are sent to the external world without making use of the brain's normal pathways of peripheral nerves and muscles [Wolpaw et al., 2002]. Primarily (consumer-grade) BCI's are based upon non-invasive Electroencephalography (EEG) measuring the electromagnetic field generated by neurons firing inside the brain. In such an EEG-based BCI the messages that a subject sends are encoded in the EEG activity (i.e. the electromagnetic field generated by the brain). Other technologies include invasive methods like Electrocorticography (ECoG) that measures similar signals as EEG but from within the skull, or methods that require advanced hardware such as Magnetoencephalography (MEG), functional magnetic resonance imaging (fMRI) or near-infrared spectroscopy (NIRS). In this project, the focus is on EEG based BCI rather than any of the other commonly used technolo-

[1] continue reading on this topic here: `blog.neuroelectrics.com/8-reasons-why-affective-computing-should-be-multimodal-and-include-eeg/`

gies. For BCI and Games a lot of different interaction paradigms have been used over the recent years, they roughly divide into motor-imagery, bio-/neurofeedback and (visually) evoked potentials [Marshall et al., 2013].

2.1 Motor Imagery

Motor imagery, also sometimes referred to as imaginary movement, describes the method of reading activation signals in the motor cortex related to (imagined) muscle activity. From the spatial information of the signal one can correlate the source in the motor cortex and can interpret the related muscle group. Motor imagery allows relatively fine control, but requires extensive training, unless used with ECoG or fMRI, rather than EEG.

In a series of experiments, a team investigated motor imagery as control paradigm. Participants were able to control a humanoid robot at a remote location (in a pilot study [Cohen et al., 2012]) or a 3D avatar [Cohen et al., 2014] using motor imagery, detected by use of a region of interest based approach inside an fMRI scanner. The participants were immersed into a virtual reality while they were inside an fMRI scanner and could control their ingame character from a third person perspective by imagining left/right hand movement to turn the character to either side and feet movement to move forward. Given different tasks, such as free movement, following a lead and simple navigation to face a specific object in the room. Participants could quickly adopt to different time-to-feedback's (TTF), this measure was introduced in this paper because of the low scanning speed of fMRI scanners (in this case a scan was made every 2s), such that feedback at time t represents the intention of the subject at time t-d. Participants perceived there performance to be best at TTF=4s, while objective measures show higher performance at 6 or 8 seconds. This TTF approach was developed after previous research indicated that participants receiving continuous feedback tend to perform worse than those who got intermittent feedback.

A different approach for the use of motor imagery as a game controller was made by [Coyle et al., 2017] with the CircleTime controller. This controller presents a spinning circle , that has three control options to choose from. The controller spins continuously and is stopped by the user imagining hand movement. This control paradigm was successfully tested in two different games with both able bodied and users with a physical impairment and is proposed by the authors as a possible standard controller used for all different kinds of interactions, which would lower the threshold for game developers to create games for BCI as well as improving usability for players, as skills acquired in one game would translate to other BCI games.

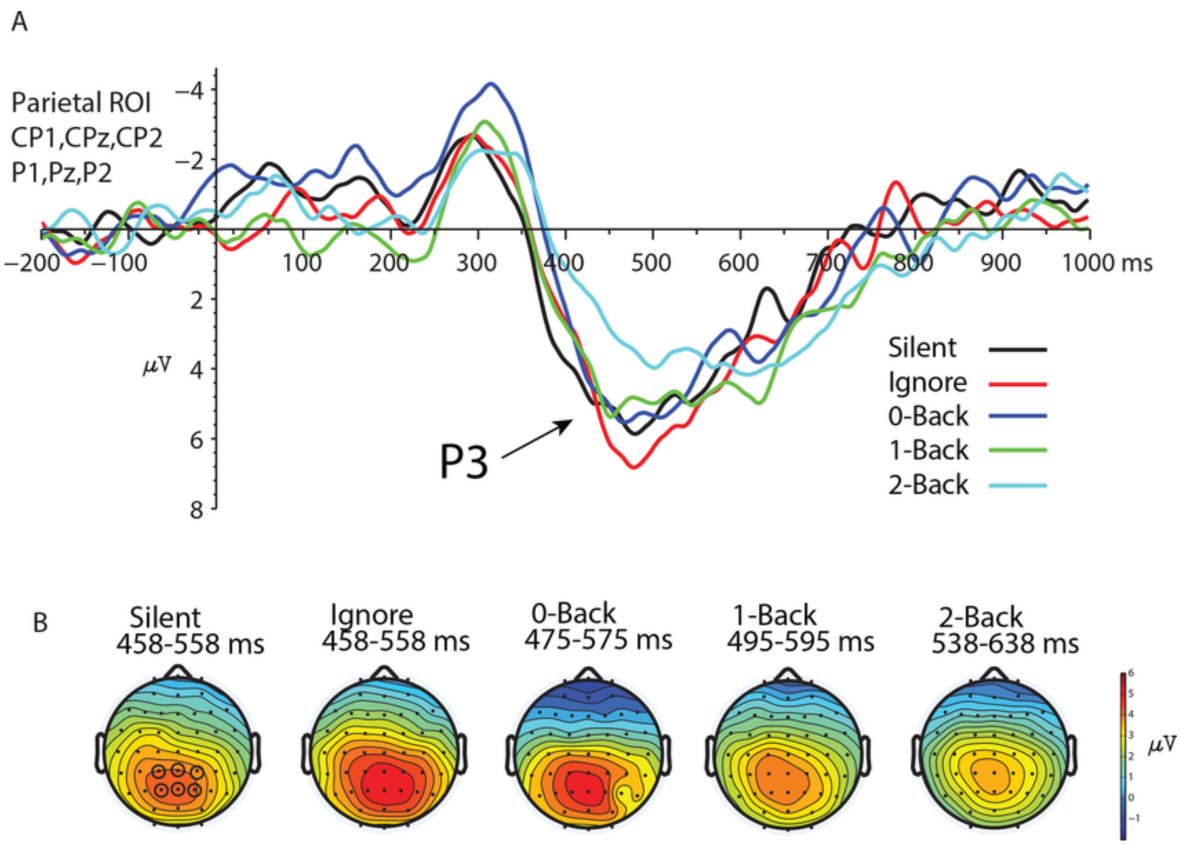


Figure 2: example plots of P3 event-related potentials recorded using EEG

2.2 Event-related potentials

Event-related potentials (ERP) are responses by the brain reacting on external stimuli, these can be sensory, cognitive or motor events[Cecotti and Ries, 2017]. There are different forms of ERP's, some based on detecting a periodic stimulus in the region of the brain that processes it, these are called steady state evoked potentials (e.g. SSVEP, see section 2.2.2), while others detect a potential representing a cognitive response, such as P3, N4 or Mismatch Negativity [Petten et al., 2005].

2.2.1 P3

P3 (often also referred to as P300) is a recognition signal, the user recognizes a keyword or an image of an object or a person, timing and amplitude tend to differ depending on the relation between the subject and the recognized stimulus. The name P300 refers to it being a Positive potential at around 300ms after the stimulus presentation, but is also commonly shortened to P3 as it is also the third response wave after stimulus onset. It was first detected in 1965 by [Sutton et al., 1965]. Nowadays, there are two separate forms of P3 responses known, the P3a, also called novelty P3, which represents a response to a novel stimulus, such as in the 3 stimulus

Figure 3: Example of a P3 speller application, by VU Amsterdam. The system can be seen working at https://youtu.be/wKDimrzvwYA

oddball paradigm, and the P3b, which is a response to recognizing a task-relevant stimulus. Brain activity models suggest that the stimulus information is maintained in the "working memory" of the frontal lobe and is monitored by anterior cingulate structures. The P3a could then be generated by the activation patterns in the anterior cingulate and related structures, whenever the focal attention is disrupted by stimulation with a distractor or the target stimulus. The attention-driven neural activity signal could then be transmitted towards the tempo-parietal region, where the engagement of memory related activities generate a P3b in the tempoparietal cortical structures [Polich, 2007].

A common application of P3 based BCI-systems are the so called P3-spellers, these are systems that show users a matrix of the alphabet and highlight it row for row, if the intended letter is in the highlighted row, the system detects a P3 response and then highlights each letter individually until another P3 response is detected for the intended letter (see figure 3 or https://youtu.be/wKDimrzvwYA [2]). This kind of system allows people with severe motor disabilities up to the point of patients with locked-in syndrome to still communicate with the outside world. However these spellers are very slow (in the range of 3-5 selections/letters per minute[Brunner et al., 2010]for latin letters, studies with the Chinese alphabet achieve approximately 1 letter in 60-120s[Minett et al., 2012]) and therefore are really only a viable option if there is no other, faster way of communication possible.

With the rise of advanced machine learning and data analytics techniques the detection of P3 responses moves away from requiring many repetitions of the stimuli and then evening out over them towards being able to detect the potential after a single trial. [Cecotti and Ries, 2017] present a way of temporal and spatial filters

[2] A tutorial on how to use this speller is available at http://www.nbtwiki.net/doku.php?id=courses:brain-computer_interfaces

(PCA and ICA filters) and a linear classifier to reliably detect a P3 after a single trial. This was achieved by using the xDAWN based spatial filter, which is based on using QR factorizations and singular value decomposition to estimate the evoked subspace [Rivet et al., 2009] and a linear classifier that is trained including artificially shifted samples. In their tests this achieved single trial accuracies of up to $\sim$ 94%.

2.2.2 Steady State Visually Evoked Potentials

The concept of Steady State Visually Evoked Potentials (SSVEP) is fairly straightforward, the user is presented with different areas in his field of view that blink at different frequencies and by focusing on one over the others, the user selects a certain option. Which field was selected can be detected by measuring the frequency spectrum of the signals in the occipital lobe (the area of the brain primarily responsible for vision). The selected frequency should have the highest signal strength. This paradigm is commonly used in spellers (like P3) and finds application in rudimentary game controllers (up/down/left/right) by sticking blinking LED's on either side of the screen or presenting blinking area's on the screen. The performance of SSVEP is limited by the fact that it takes a sample of several second to detect a signal and the fact that the usable frequency range is limited by the capabilities of the human vision (effectively $\sim$5-20Hz) and the difficulty of distinguishing different frequencies if they are too close to each other, as well as the additional challenge, that users respond differently to certain frequencies and each system needs to be "fitted" to the user. The performance of such a speller system can be improved by using probability models, such as Bayes or Markov models, predicting the most likely series of letters. Users can therefore select the most probable letter quicker than less probable letters (the probability of a letter is based on common letter combinations and letter orders in the English language) and therefore increasing the average input speed (which is generally still in the range of ¡10 letters per minute[Hwang et al., 2012] [Higger et al., 2016][3].

2.3 Passive BCI

A passive BCI is one that derives its outputs from arbitrary brain activity arising without the purpose of voluntary control, for enriching a humanmachine interaction with implicit information on the actual user state [Zander and Kothe, 2011].While many forms of BCI interaction rely on the user actively manipulating his brain activity in order to control a system, e.g. focusing on a stimulus for SSVEP or actually cre-

[3] An example of the workings of the speller seen in figure 4 can be found on `https://youtu.be/JNFYSeII0rw`

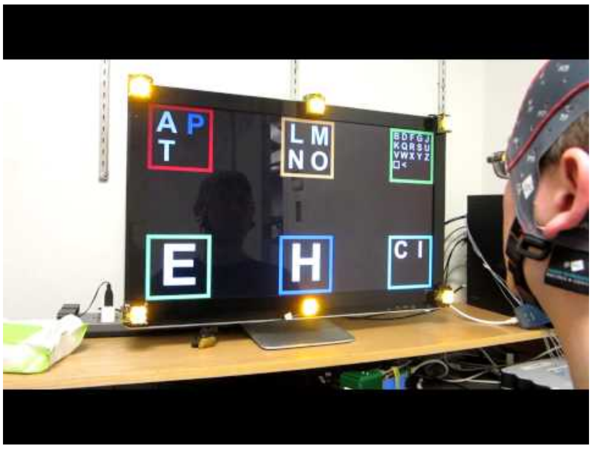


Figure 4: Example of an SSVEP speller application, [Higger et al., 2016]

ating brain activity with motor imagery, there is another form of implementing a BCI into a system without requiring the user to use explicit control, but that passively detects information about the users mental state which then can be used for implicit interaction [George and Lecuyer, 2010]. Aspects of the mental state that are commonly monitored using passive BCI techniques are the users task engagement, the mood and emotion, error recognition, relaxedness and mental workload [George and Lecuyer, 2010]. This also includes detection of Error Potentials, which can be used to improve the performance of active BCI applications such as P3 spellers, by providing fast feedback for misclassification [Dal Seno et al., 2010].

2.3.1 Emotion detection

One of the fields of passive BCI is the detection of emotions through a BCI. Doing this has applications in several fields, for example affective computing, but also as a feedback loop for BCI games. This way, a game could use detecting the users emotions in order to improve the immersive game experience and create a personalized game experience to make the user experience the intended emotions, or attempt to keep the user in a constant flow state by adjusting the difficulty of the game to keep the players attention and frustration levels in balance.

The team of [Reuderink et al., 2012] describe a hemispheric system based upon the three-dimensional extension of the Russell circumplex of affect, which posts a 3-dimensional space with the axes pleasure, arousal and dominance, often referred to as the PAD-model. From a literature review the researchers mapped the 3 dimensional affect space to activities in different frequency bands over different hemispheres of the brain. Activity in the right-hemisphere is related to emotion recognition (right hemisphere theory), while regions in the left and right frontal cortices are associated with positive and negative emotional states (valence theory, based on

Dimension	*Delta*	*Theta*	*Alpha*	*Beta*	*Gamma*
Valence ↑	$H_{v\delta}$: fron.-med. ↑	$H_{v\theta1}$: l-hemi. ↑ $H_{v\theta2}$: r-hemi. ↓ $H_{v\theta3}$: fron.-med. ↑	$H_{v\alpha1}$: l-hemi. ↓ $H_{v\alpha2}$: r-hemi. ↑	–	$H_{v\gamma1}$: l-temp. ↓ $H_{v\gamma2}$: r-temp. ↑
Arousal ↑	$H_{a\delta}$: posterior ↑	$H_{a\theta}$: posterior ↑	$H_{a\alpha2}$: global ↓ $H_{a\alpha1}$: frontal ↑	$H_{a\beta}$: parietal ↑	$H_{a\gamma}$: gamma ↑
Dominance ↑	–	–	–	–	–

Figure 5: Correlates for valence, arousal and dominance in the frequency domain, [Reuderink et al., 2012]

[Silberman and Weingartner, 1986, Tucker, 1981]). Alternative to the valence theory, the approach/withdrawal theory, originally described by [Davidson, 1992], is being presented. According to this theory, different hemispheres are activated in different ways depending on the motivational direction of the emotional state. Activity in the left frontal hemisphere is associated with approach, while activity in the right hemisphere is associated with withdrawal. The correlates for the third dimension of the emotional space, Dominance, has so far been less researched and cannot yet be conclusively linked to certain areas or frequency bands. [Heraz and Frasson, 2007] has found negative correlations with the alpha, beta, delta and theta band, which allowed for a classification accuracy of the dominance dimension of 0.75 (kappa statistic). Between both theories there is overlap, due to the fact that most approaching emotions are associated with positive feelings, while emotions of withdrawal tend to be associated with negative feelings.

This lead to the hypotheses that are described in figure 5. These hypotheses have than been tested in a game setting through the "Affective Pacman Game" [Reuderink et al., 2009], in which different emotions were evoked in a natural way, such as frustration through neglecting (part of the) user input.

In order to filter out common and known attributes and noise, the raw signal was filtered so that signals below 0.2Hz and the powerline noise on 50 Hz were filtered out, then the leftover signal was correlated against the data from the EOG sensors, that measured movement of facial muscles, such as eye blinking, according to the technique described by [Schloegl et al., 2007], that works as follows: A measured signal Y(t,ch) consists of the actual EEG signal S(t,ch) + 3 dimensions of EOG activity with their respective weight vectors,

$$Y(t, ch) = S(t, ch) + [EOG1(t), EOG2(t), EOG3(t)][b1(ch), b2(ch), b3(ch)]^T$$

which can be rewritten in matrix form to span over all channels, as

$$Y_{TxM} = S_{TxM} + N_{Txn} b_{nxM}$$

with T being the timepoints, M the number of channels and n the components of the noise signal (U). In order to obtain the original signal, the formula can be rewritten as $S = Y - U * b$, which requires the knowledge of the noise source U and the respective weighting factors b, thus the EOG noise source has to be recorded separately. In order to obtain the weighing factors b, it is assumed that S and U are uncorrelated, which leads to,

$$U^T S = U^T * Y U^T U * b$$

which, because of $U^T S = 0$, results in

$$b = U^T U^{-1} U^T Y = C_{NN}^{-1} C_{NY}$$

with C_{NN} being the auto-covariance matrix of the EOG channels and C_{NY} being the cross-covariance between the EEG and EOG channels. Therefore the EEG signal can be corrected for EOG noise by using

$$S = YUb$$

In order to obtain definitive and sufficiently large EOG recording, the participants were asked to perform several tasks with their eyes before the actual experiment started, which have been recorded for reference. The participants had to first roll their eyes clock-and counter-clockwise several times using their entire field of vision without moving their head and then blink rapidly for a short time. Another recommendation by [Schloegl et al., 2007] is the implementation of a saturation detection on the AD converter and the amplifier and mark all values that caused saturation to be saved as NaN (not a number), according to the IEEE 754 standard. When attempting to detect emotions based on asymmetry measures, the naive analysis of asymmetries between the left and right hemispheres has a number of pitfalls as the correlation between the corresponding electrodes on both sides are high (which was demonstrated by showing how, when knowing one of the signals, one can predict the other using relatively simple regression models)[Allen et al., 2004].

In order to have sufficient baseline data for later signal analysis, researchers regularly use the rule of thumb of recording exactly 8 minutes of the patient in a resting state. [Allen et al., 2004] reasons that, depending on the number of variables being observed, it is possible to deal with a smaller set of baseline data. Furthermore he states that, for recording the resting state baseline it is more advantageous to measure more, shorter blocks, rather than fewer longer blocks, based on calculating Cronbach's alpha over them. It is further recommended to report measures of internal consistency along the results.

[Allen et al., 2004] divides EEG asymmetry into three different effects that need to be distinguished in order to make claims about the origin and the meaning of the observation. The stable trait asymmetry appears to be characteristically for a subject and is stable and present over multiple sessions, while occasionally specific asymmetries are different over multiple sessions, but consistent within each session. A possible explanation of these effects is the subjects mood on the day of the experiment and it can be canceled out by averaging over multiple sessions. The state specific asymmetry is what is for most experiments the intended measure, namely the difference in asymmetry between experimental conditions.

Another important aspect of analyzing EEG data is the choice of an adequate reference, the influence of which appears to actually be more significant than the influence of the exact amount of collected resting data and other artifacts[Smith et al., 2017]. The team did an empirical analysis of the differences in readings caused by the reference scheme and concluded, that, for most measurements, the Cz electrode reference is disadvantageous as it tends to overlay activities at all other sites with the activity at Cz location and thus masking other effects. The linked mastoids reference scheme allows for relatively clear observation of the medio region, while masking activities on the outer hemispheres and the commonly used average reference is limited by the equal spreading of electrodes across the head and should not be used in cases where electrodes are montaged asymmetrically or too small amounts of electrodes are used. The recommended referencing scheme especially for asymmetry measures is the current source density (CSD) schematic. CSD is a mathematical transformation (second order spatial derivative; Laplacian) providing a representation of the direction, location and intensity of current generators. CSD maps represent the magnitude of the current flow entering (sinks) and leaving (sources) the scalp. The CSD analysis is a reference-free technique that provides topographies with more sharply localized peaks than those of the scalp potential, while eliminating volume-conducted contributions from distant regions [Kayser and Tenke, 2006].

For noise removal it has proven effective to use an Independent Component Analysis (ICA) on the obtained data and then attempt to identify which components are noise and which contain the actual signal. This is done by analyzing the characteristics of the signal, e.g. unphysiologically large signals are likely to stem from muscle activity, such as eye movements. ICA proves to be effective, even though it relies on assumptions and prerequisites that are not fully met. It is assumed that the propagation delay between electrodes is negligible, which can be relatively safely assumed to be the case, as the temporal resolution of the EEG measurement is much lower than the propagation time. Further, it is assumed that the signal sources are stationary in terms of topography, which does not seem to be true [Onton et al., 2006]. The time courses of the sources are assumed to be independent, though there are covariations between eye blinks and P300 (surprised blinking in response to a stimuli) and alpha bursts (closing the eyes increases alpha

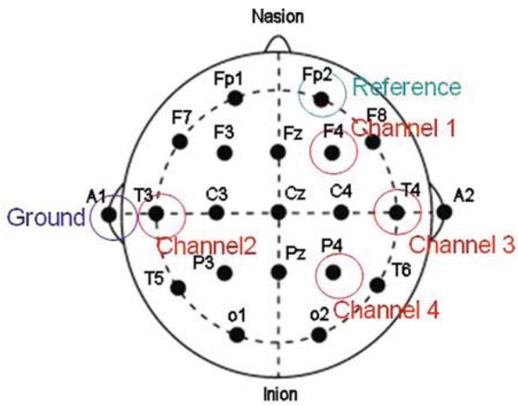


Figure 6: Electrode placement for emotion detection, image courtesy of [Li et. al., 2009]

activity in the occipital lobe). Lastly, ICA assumes a smaller or equal number of sources and sensors, which is not determinable from the current understanding of the brain, though [Artoni et al., 2014] concluded that in a typical EEG recording they could identify as few as 15 reliable sources [Smith et al., 2017].

A different approach for emotion detection was developed by [Li et al., 2009], who developed a system that is based upon features developed by [Takahashi, 2005] and [Picard et al., 2001]. While [Takahashi, 2005] and [Picard et al., 2001] relied on using multiple channels of biosignals, such as skin conductance, electromyography and heart rate sensors, [Li et al., 2009] proposed a system that only required EEG, rather than other measures, but still extracted similar features from the raw data. This paper is mainly a demonstration of the fact that data from a minimalistic setup with only 6 electrodes with simple feature extraction can already be used for emotion classification, though be it with slightly lower accuracy than other more complex methods.

The team recorded EEG on four dry electrodes located on position F4, T3, T4 and P4 according to the international 10-20 standard. The reference electrode was placed on Fp2 and the ground was located at the left ear lobe (A1) . In the following $\bar{X}$ is defined as the normalized signal (zero mean, unit variance) of signal X:

$$\bar{X}(t) = \frac{X_n - \mu_X}{\sigma_X}$$

This system is based upon extracting the following 6 features from the original signal: the mean of the raw signal X:

$$\mu_X = \frac{1}{T}\sum_{t=1}^{T} X(t)$$

the standard deviation of the raw signal X,

$$\sigma_X = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(X(t) - \mu_X)^2}$$

the means of the absolute values of the first differences of the raw signal X

$$\delta_X = \frac{1}{T-1}\sum_{t=1}^{T-1}|X(t+1) - X(t)|$$

the means of the absolute values of the first differences of the normalized signal $\bar{X}$

$$\bar{\delta}_X = \frac{1}{T-1}\sum_{t=1}^{T-1}|\bar{X}(t+1) - \bar{X}(t)| = \frac{\delta_X}{\sigma_X}$$

the means of the absolute values of the second differences of the raw signal X

$$\gamma_X = \frac{1}{T-2}\sum_{t=1}^{T-2}|X(t+2) - X(t)|$$

the means of the absolute values of the second differences of the normalized signal $\bar{X}$

$$\bar{\gamma}_X = \frac{1}{T-2}\sum_{t=1}^{T-2}|\bar{X}(t+2) - \bar{X}(t)| = \frac{\gamma_X}{\sigma_X}$$

where t,T are the sampling number and the total number of samples, respectively. This way 6 features are extracted per channel, providing a total of 24 features (in this case). The team then used a relevance-vector machine for classification and compared that with other classification algorithms available in WEKA[4]. From their analysis the team concludes that for all channels the most important features are δ_X and γ_X. The team managed to achieve an accuracy of 97.8% to distinguish between the states Happy, Sad and Relaxed using all 24 features and still achieved about 94% accuracy when just selecting the 8 most informative features (δ_X and γ_X on all 4 channels), which resulted in a 4.5 times faster training time. It could therefore be considered to drop the additional features when the resources for computation are constrained.

A rather different approach was taken by [Lee and Hsieh, 2014] who attempted emotion classification based on functional connectivity patterns, thus exploring the data for intrabrain synchronization, correlation and coherence between dyads of electrodes. The team did so by first extracting three new features from the 64

[4]Weka is an open-source machine learning and data mining application available at `http://www.cs.waikato.ac.nz/ml/weka/`

channel EEG data, a correlation factor between each possible pair of electrodes at frequency f

$$r(f) = \frac{C_{AB}(f)}{\sqrt{C_{AA}(f)C_{BB}(f)}}$$

with C_{AB} is the cross-covariance between signal A and B and C_{AA} and C_{BB} are the auto covariances of signal A and B respectively. The correlation factor r(f) can therefore take a value between -1 and 1 where a higher r(f) corresponds with a stronger relationship between the electrodes. The phase synchronization index between two nonlinear oscillation systems is defined as

$$\varphi_{n,m} = |n\varphi_1(t) - m\varphi_2(t)| < \alpha$$

where φ_1 and φ_2 are the phases of the two oscillation systems and α is a constant. In order to use this, the instantaneous phase of each signal first needs to be computed using

$$\varphi_t = \arctan \frac{x_H(t)}{x(t)}$$

where $x_H(t)$ is the Hilbert transform of x(t). After obtaining the instantaneous phases of two signals the phase difference can be obtained by setting m=n=1. For two signals consisting of L samples, phase synchronization index (PSI) is defined as

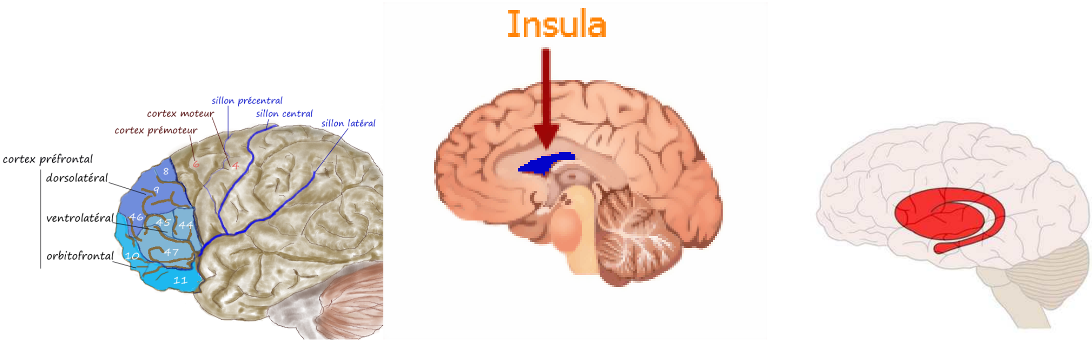
$$PSI = \left| \frac{1}{L} \sum_{t=0}^{L} e^{i\varphi(t)} \right|, i = \sqrt{-1}$$

The PSI is sensitive to phase change and has a range from 0-1 where 1 is only achieved in case of a strict phase-lock and 0 represents a uniform phase distribution. In the experiment participants watched emotional movie scenes taken from the Standard Chinese Emotional Film Clips Database and were asked to indicate via button press if this movie scene caused an emotion change for them. The participants emotions were measured using a self assessment mannequin test in order to label the obtained emotion. The resulting feature space was then reduced to features for which ANOVA returned $p \geq 0.05$. The resulting featureset was then analysed using a Quadratic Discriminant Analysis (QDA) classifier. Based upon [Brodersen et al., 2010] the point was raised that averaging accuracies often leads to unclear results and that a balanced accuracy should be used. This balanced accuracy is calculated using

$$\frac{1}{2}(\frac{TP}{P} + \frac{TN}{N})$$

Where $P = TP + FN$ and $N = TN + FP$(abbreviations see footnote[5]).

[5]Abbreviations: TP:true positive; FP:false positive; TN:true negative; FN: false negative; P: positive; N: negative



(a) medial orbitofrontal cortex, ventromedial prefrontal cortex

(b) insula

(c) striatum

Figure 7: Locations of the neural correlates for the chameleon/social mirroring effect

2.4 Hyperscanning - Inter-brain connectivity

Hyperscanning is a technique in which brain data from more than one subject are being collected (through the same methods/machines as other BCI paradigms) but instead of the users mental state being interpreted as standalone data, it is being connected to the mental state of a second subject that is in social interaction with the first subject [Montague et al., 2002].

In order to investigate social interaction, one cannot see the brain as a single standalone object but has to view it in context of other brains that it is interacting with. By analyzing the correlations of interbrain phase-locking and synchronizations, one can learn about the interaction between both users [Schilbach et al., 2013a, Schilbach et al., 2006].

In order to estimate the relation between two subjects, psychology has already been investigating, among others, the chameleon effect, which implies that subjects that like each other, and/or that are in a relation with one another, seem to have a tendency of copying each others movements, but also use similar movements and gestures subconsciously, an effect known as the chameleon effect or social mirroring [Bramoull, 2007, Chartrand and Bargh, 1999, Kendon, 1970].

[Kuehn et al., 2011, Kuehn et al., 2010] investigated the neural correlates of this effect and came to the conclusion that the effect seems to originate in the medial orbitofrontal cortex (mOFC), ventromedial prefrontal cortex (vmPFC), the striatum, and the insula (see fig.:7).

[Dumas et al., 2011, Dumas et al., 2010] executed EEG hyperscanning experiments with dyads in a social interaction under three different conditions. In the first condition, both participants were asked to follow the movements and gestures on a video taken from the Library of 20 Intransitive Hand Movements (LIHM). Then participants took turns in following/ leading each other. The data obtained was then re-referenced to the common average reference (CAR) and split up into the different frequency bands theta (4-7Hz), alpha-mu(8-12Hz), beta (13-30Hz) and gamma (31-48Hz) using discrete Hilbert methods. The interbrain analysis was then executed for each corresponding electrode pair (j and k) on the separate caps using the phase-locking value according to the following relation:

$$PLV_{j,k} = \frac{1}{N} \left| \sum_{t=1}^{N} e^{i(\phi_j(t) - \phi_k(t))} \right|$$

with ϕ being the phase and || the complex modulus, thus PLV equates 1 if both signals are perfectly locked across the entire observation window and 0 if they are completely unsynchronized. To investigate the relations between electrodes further, the authors distinguish three different forms of neighboring electrodes, which is coupled up for further analysis:

- two side-by-side electrodes on the cap of subject 1 connected to two side-by-side electrodes on subject 2
- one electrode on the cap of subject 1 connected with 2 side-by-side electrodes on the cap of subject 2
- one electrode on the cap of subject 2 connected with 2 side-by.side electrodes on the cap of subject 1

Based on these groupings of pairs of electrodes, the clusters were further analyzed. As cluster statistic, the sum of all t-values of all members of a ”neighbourhood” was used and comparison procedures by bootstrapping the cluster statistics were performed on them.

The statistics were corrected through spatial and spectral dimensions by using the maximum t-value for each permutation. Increased synchronizations were found in different frequency spectrums, in the alpha-mu band, the subjects showed synchronizations between the right centro-parietal regions in both subjects. In the beta band, there was synchronization visible between the leaders central region with the followers right parieto-occipital regions and in the gamma band the leaders centro-parietal region appeared to have synchronized with the followers parieto-occipital region (see fig.:8).

[Szymanski et al., 2017] have investigated a neural correlate for social facilitation by studying inter-brain phase synchronization in a cooperative task. The authors propose joint attention situations as an experiment set-up paradigm that best enables a separation of experimental conditions as it does not require motor output for the task at hand. The participants were asked to find certain ”target objects”

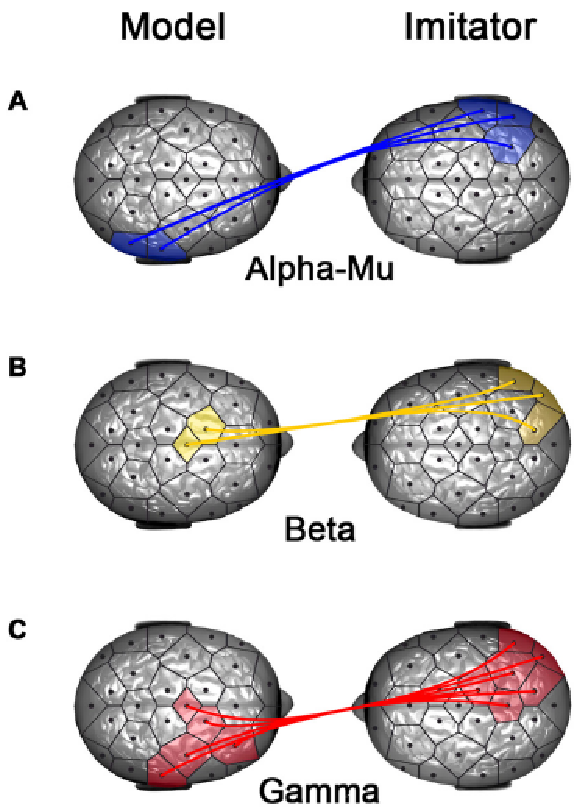


Figure 8: Intersubject neural synchronizations during interactional synchrony. coupling PLV for all participants between electrodes of the model and the imitator. On the left of the figures the participants are models, on the right the participants are imitators. A. Alpha-Mu band cluster between right centro-parietal regions. B. Beta band cluster between central and right parieto-occipital regions. C. Gamma band cluster between centroparietal and parieto-occipital regions. [Dumas et al., 2010]

from pictures of shelfs that also contained numerous ”distractor” objects, either on their own in an individual condition or together with a partner in a social condition. For every image one of the participants has to respond by typing in the number 0,1 or 2 depending on how many target objects the participants spotted. The role of responding participant is switched halfway through the experiment. The participants were free to interact with one another in any form of their choosing, but were asked to minimize the amount of movement in order to prevent too large artifacts in the measurement. The data was preprocessed through an off-the-shelf ICA implemented in the Brain Vision Analyzer 2. The cleaned signal was then approximated using complex Morlet wavelets in the range from 2-20Hz in 2Hz steps and then two synchronization measures, the inter-brain phase coherence (IPC) and the phase-locking index (PLI) were calculated. PLI reflects the invariance of phases at a single electrode across N trials in the time-frequency domain, where $\varphi_k^n(t, f)$ is the phase of the n-th trial at time t and frequency f of an electrode k.

$$PLI_k(t, f) = \left| \frac{1}{N} \sum_{n}^{N} e^{j\varphi_k^n(t,f)} \right|, j = \sqrt{-1}$$

The IPC represents the degree of constancy in phase difference across N trials between two electrodes measured from one or two brains simultaneously.

$$IPC_{kl}(t, f) = \left| \frac{1}{N} \sum_{n}^{N} e^{j\Delta\varphi_{kl}^n(t,f)} \right|, j = \sqrt{-1}$$

with the phase difference between electrodes k and l at trial n, time t and frequency f being equal to

$$\Delta\varphi_{kl}^n(t, f) = mod(\varphi_k^n(t, f) - \varphi_l^n(t, f), 2\pi)$$

and the phase φ being calculated as

$$\varphi_1^n(f_n, t) = arg\,\{y_1^n(f_n, t)\}$$

and

$$\varphi_2^n(f_n, t) = arg\,\{y_2^n(f_n, t)\}$$

which stems from a Gabor expansion of the data in each epoch into a complex time-frequency signal $y(f_n, t)$. The coefficients span a $m \times n$ matrix where m is frequency (.33Hz resolution) and n is time (1ms resolution)[Lindenberger et al., 2009].

Grand averaging across pairs shows increased PLI and IPC in the frontal regions for lower frequencies in the social condition. It is concluded that dyads who have high IPC during individual attention tasks, but do not align their cognitive processes beyond a certain level during teamwork benefit the most from working in a team [Szymanski et al., 2017].

[Saenger et al., 2012] has presented an experiment in which the interaction between 2 guitar players are being investigated. The team reproduced an earlier experiment of their research group [Lindenberger et al., 2009], which showed increased synchronization between guitar players especially in the onset period. While in the original research both guitar players played the same piece in unison, in the new experiment the guitarists played different voices of the same song, thus excluding the possibility that the synchronization only stems from playing the same song but appears to stem from a deeper underlying neural cause. Like the previously presented paper, this research uses PLI and IPC to investigate the hyperscanning correlations. The data shows an increase in phase synchronization, as was in the early onset phase of the duet, during which the tempo and other aspects of the music are being coordinated between leader and follower. This increased synchronization happens mostly in the frontal and central electrode sites. The team used methods from graph theory to investigate the intra- and inter-brain phase coherence in greater detail (investigating node strengths, small-world properties and community structures). They found a difference in node strengths between the follower and leader role, which might be attributable to the different cognitive states between following and leading, according to the researchers, which could be attributed to effects similar to those observed by [Dumas et al., 2010], where different regions of the brains of follower and leader would synchronize.

[Pan et al., 2017] have investigated the neural correlates of social relations in an fNIRS- hyperscanning study in which male-female dyads in three different categories (strangers, friends, lovers), were asked to play a cooperative game with/against each other. In order to obtain data about their brain activity, both subjects are connected to a 3x5 matrix of fNIRS probes, the middle of said matrix was placed on top of the C4 location according to the international 10-20 scheme, measuring activity in the right fronto-parietal region. The signal was then processed using a principal component analysis (PCA) using Gaussian spatial filtering. The frequency range observed in this study was fNIRS typically low, between 0.08Hz and 0.31Hz. For each pair of corresponding channels (same probe location on both subjects), an interpersonal brain synchronization factor is being calculated as the mean coherence in two task blocks minus the coherence in the rest period between these blocks, according to the following formula:

$$IBS = \frac{1}{2}(IBS_{block1} + IBS_{block2}) - IBS_{rest2}$$

These values were then converted to z-statistics and tested in a one-sample t-test. If a channel turned out significant from the IBS, a one-way ANOVA was calculated on that IBS. The synchronizational direction was investigated using a Granger causality analysis (GCA) using a vector autoregressive model that measures the causal relationship between time series in the brain data. The pairwise conditional Granger-causality of both participant directions was calculated and examined using one-sample t-tests. There was a significant IBS detected on one of the channels that was located in the approximate area of the right superior frontal cortex for lover dyads, that was not observable for friend and stranger dyads.

[Bilek et al., 2015] also investigated a joint-attention interaction between 2 subjects using an fMRI based hyperscanning approach. Subjects had to communicate through pointing into the direction of a target shape by manipulation of their gaze, while their partner attempted to interpret that communication. Analysis of the data showed an increase in synchronized activity in the right tempoparietal junction.

3 Research Goal

Previous research shows that humans in social situations seem to have a tendency of synchronizing brainwaves when they feel closer to their interaction partner. There appears to be a significant difference in synchronization (right superior frontal cortex) between lovers and strangers who are engaged in a cooperative action coordination game [Pan et al., 2017] and there are also indications that hyperscanning techniques such as IPC and PLI can be used to predict team-performance [Szymanski et al., 2017]. As a single subjects emotion is expressed in modulation of the mental state and is visible in the Intra brain synchronization [Lee and Hsieh, 2014] it is hypothesized that simultaneous stimulation of multiple subjects reveals a connectivity pattern (phase-lag index [PLI]) from which predictions can be made about the subjects social relationship. The proposed research then sets out to answer the following research questions:

- Are there significant correlations (based on phase-lag index) measurable between subjects in a joint-attention task setting?
- Are there significant differences in phase-lag index measurable between different types of participant dyads (strangers/lovers)?
- To what extent can these correlations (if found) be used to automatically distinguish different types of dyads?

4 Methodology

In order to test the hypothesis on the research question, it is proposed to conduct an experimental hyperscanning study, in which participating dyads are being exposed to emotional stimuli in a joint-attention setting.

As there is evidence that synchronizations within the dyads are larger when the subjects engage in the stimulus activity more frequently [Saenger et al., 2012], a task was chosen that couples engage in on a regular basis and that allows for precise and targeted elicitation of emotion. As adult couples seem to spend about a third of their time together with watching TV[6], movie sequences as stimulus were considered such activity. During the experiment the participants sit next to each other facing a common screen, while the experiment leader can monitor everything from 2 separate screens that are not visible from the participants perspective (see figure 9 for more information).

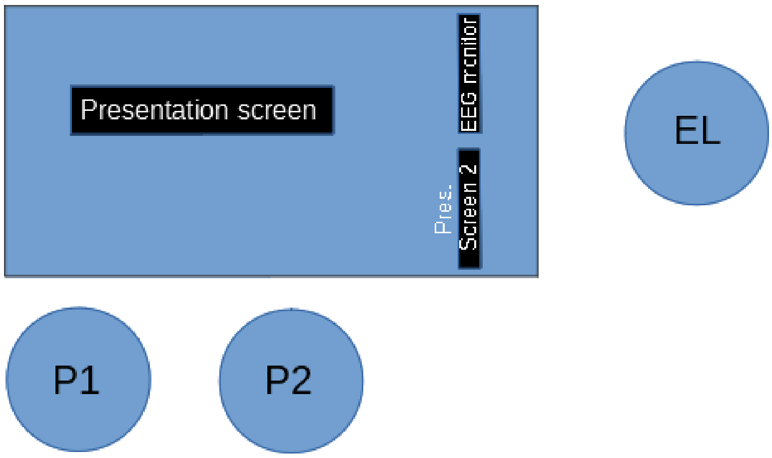


Figure 9: Experiment Setup, top-down perspective

4.1 Stimuli

The emotion eliciting stimuli are movies picked from the "FilmStim" database[7], set up by [Schaefer et al., 2010]. This database contains 64 scenes taken from French and English movies, of which the emotional content has been validated.

The chosen movie sequences are spread across the evoked emotions such that for each block of stimuli a similar distribution of positive and negative emotions is achieved. Additionally, there is a segment with neutral emotional content and each block starts with a 60s and ends with a 30s relaxation/breathing exercise period as baseline/reference. In each block there are one amusing, one neutral and two

[6] `https://www.theguardian.com/lifeandstyle/2007/jun/09/familyandrelationships` quoting the UK Office for National Statistics

[7] `http://nemo.psp.ucl.ac.be/FilmStim/`

negative sequences (fear, anger or sadness), which are chosen by availability in the database and the length of the sequence (between 15s and 5 min), as well as the emotional content. In order to confirm which emotion was actually evoked, as well as making the participants more aware of their emotions, each subject is asked to fill in a self-assessment manikin (SAM) [Bradley and Lang, 1994] in between stimuli.

4.2 Participant selection

Participation in this research is open to all healthy adults. The subjects are divided in two different kinds of dyads, the first one, ”couples”, are dyads who are living in a comitted relationship with each other, the other category are strangers, thus, participants who do not know each other so far. The participants in this research are mainly University students taken in a convenience sample from the environment surrounding University of Twente DesignLab.

4.3 Data Acquisition

The EEG data in this experiment is acquired using two separate BioSemi Active2 EEG devices, connected and synchronized via the fibre-optic based daisy-chaining capability to one computer running ActiView. This allows for both EEG's to run on a synchronized clock as well as that both datastreams get saved in the same file. Other means of synchronization therefore become obsolete. The BioSemi EEG's both run on 2 kHz (2048 1/s) sampling frequency, which is predefined for the daisy chaining mode. A second computers takes over the stimulus presentation, which is programmed using ”OpenSesame”[8]. The stimulus software sends markers at the start of the video to the EEG recording software ActiView[9] by using a button that sends keystroke signals to both computers at the same time, thus starting the stimulus presentation, as well as, sending a marker to ActiView.

Both EEG are connected to the participants using the 32+2 channel BioSemi headcap. The exact layout of the electrode locations on this cap can be found in figure: 10. The use of additional ECG/EOG channels was considered, but weighing off the advantage this brings on top of noise reduction using ICA (section 4.4.2) against the obstruction/unpleasantness for the participants during the experiment, this was not considered to be worth the discomfort.

[8]OpenSesame is a Psychology and Neuroscience software suite specialized on stimulus presentation and available under a CC BY 3.0 license: `http://osdoc.cogsci.nl/`

[9]ActiView is an open source signal acquisition software for BioSemi EEGs programmed in LabView and is available at `https://www.biosemi.com/download_actiview.htm`

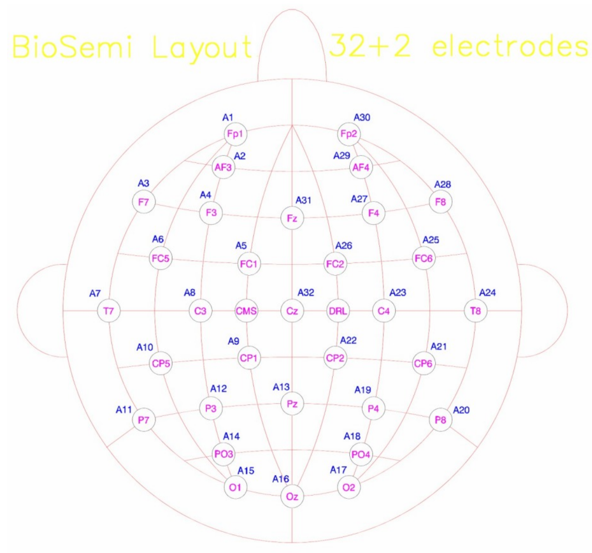


Figure 10: Electrode placement on the subject's head using the BioSemi 32+2 (DMS + DRL) headcap

4.4 Data Analysis

For the signal analysis a data-driven approach is used to analyze the results. The initial signal correction such as removing powerline and low frequency noise is done using "EEGLab"[10]. The further analysis is done in Python [11] using (among others) the MNE library[12].

4.4.1 Reference Scheme

Choosing the reference scheme for an EEG recording is crucial, as choosing the wrong scheme for the case could lead to obscuration of relevant information in the signal. [Smith et al., 2017] showed that for emotion detection in EEG the current source density (CSD) reference scheme is recommended, as it has the lowest impact on the spatial distribution of activity levels.

4.4.2 Independent Component Analysis

In order to identify and remove noise artifacts from the measured signals, an Independent Component Analysis is used.

[10] A MATLAB (`https://www.mathworks.com/products/matlab.html`) plugin, available at: `https://sccn.ucsd.edu/eeglab/`

[11] using the PyData stack (`https://pydata.org/downloads.html`), including Anaconda (`https://www.continuum.io/downloads`) and jupyter notebook (`http://jupyter.org/`)

[12] A library aimed at MEG/EEG data analysis, available at `http://mne-tools.github.io/mne-python-intro`

4.4.3 Frequency filters

As the experiment aims at finding indications for phase shifts and synchronizations across the frequency bands, the phase lag indexes for each connection are calculated for a number of fine grained frequencies and then averaged across the main frequency bands (see table 1).

4.4.4 Epoching and Baselining

As the experiment contains different phases during which a stimulus is either present or not present and because for many measures it is necessary to compare the reactions to a specific stimulus, the continuous EEG recording is split up into so-called Epochs using markers sent by the presentation computer. Each marker is followed by exactly 15s of no-stimulus time, followed by the presentation of a stimulus. Additionally every stimuli-block contains a 60s (in the beginning) and a 30s (in the end) breathing exercise phase during which no stimulus is present. An Epoch can therefore be either one of two categories,

1. 15s of no-stimulus, followed by 0:16-4:30min of stimulus time
2. no-stimulus, either 30s or 60s long

4.4.5 Synchronization measures

After splitting the data into separate frequency ranges using narrow bandpass filters, the primary feature Interbrain phase coherence for the same and neighbouring electrode locations on both helmets will be calculated using the "weighted phase lag index" as described by [Vinck et al., 2011] [13] As some fMRI studies suggest, synchronizations can be causally linked between different brain regions, the measures are calculated between all possible electrode site locations (that includes both inter and intrabrain connectivity) to gain the maximum amount of knowledge from the data [Dumas et al., 2010]. Additionally, research on intrabrain synchronization showed, that multiple distinct regions of the brain seem to be involved with the emotional state [Lee and Hsieh, 2014].

[13] implemented in MNE http://martinos.org/mne/dev/generated/mne.connectivity.spectral_connectivity.html

4.4.6 Significance testing

The difference between the two conditions (strangers/couples) is investigated using a non-parametric permutation cluster test[14] that was developed and implemented by [Maris and Oostenveld, 2007].

4.5 Experiment planning

The experiment consists of one session of approximately 2 hours per dyad. The session is split in several periods. The experiment conducted in this research has been approved by the University of Twente, Faculty of EEMCS Ethical committee.

4.5.1 Information and intake

In this first information and intake period, participants receive information about the research they are participating in (see Appendix B, for the provided information) and get the chance to ask questions they have about the research. The participants are also explicitly informed that the video stimuli that are being presented contain scenes that may be shocking for some people and that they are free to stop the experiment at any given time if the scenes are too much for them. Afterwards they are asked to fill in a short demographic questionnaire[15]. Once participants have completed these steps the preparation phase for the actual experiment starts.

4.5.2 EEG preparation

In this phase the EEG measurement is prepared, that means, one after another, participant's head sizes are measured and the appropriate size of cap is selected and put on the participant's head. Afterwards the electrodes are connected to their respective locations as shown in figure 10 and the connectivity controlled in ActiView. Before the next phase of the experiment is entered, participants get the chance to stretch their legs and, if necessary, visit the bathroom before the measurement starts.

4.5.3 Stimulus presentation phase

In this phase of the experiment the participants watch the stimuli that were described earlier. There are three blocks of stimuli, each block starts with a 60s breathing exercise and afterwards four video clips, of which two induce negative emotions

[14] more information about the exact test can be found here: `http://martinos.org/mne/stable/generated/mne.stats.permutation_cluster_test.html`

[15] available at: `https://goo.gl/forms/mOKx9feYvyyXgDQg2`

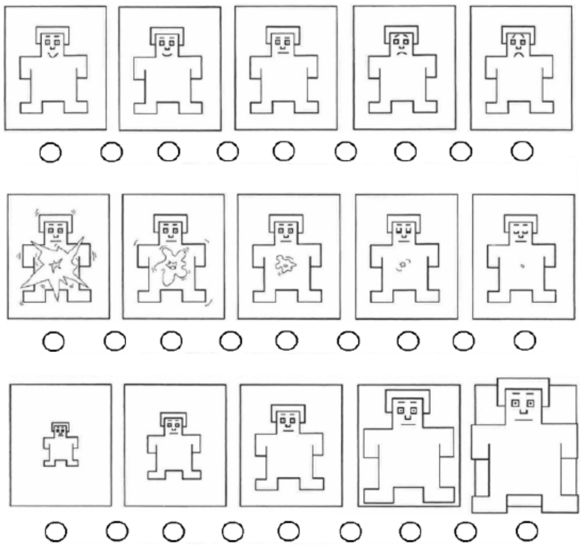


Figure 11: Self Assessment Manikin (SAM) test for (top to bottom) Pleasure, Arousal and Dominance

(sadness/anger), one induces a positive emotion (Happy/Funny) and one has no measurable emotional content. After every video clip the presentation stops shortly to allow for the participants to fill in a short SAM test (see fig.: 11) and the experiment leader presses a button to confirm completion of that when it's done and the presentation continues with a 15s quiet period during which only a centering cross is visible on the screen. In this phase the experiment leader closely monitors the participants reaction to the stimuli and will stop the experiment in the case of a participant getting clearly shocked, or when a participant indicates being unable to handle the stimulus. During the 15s no-stimulus phase, a centering cross is presented on screen, during the breathing exercise the cross is replaced by the sentence "Please focus on breathing in and out calm and steady".

4.5.4 Final phase

In this final period of the experiment all measurements have already been completed. The participants get disconnected from the EEG devices and get the chance to clean themselves, after which they are offered the chance to ask more questions about the experiment and the research behind it.

5 Results

In order to investigate the research question by experiment, an exploratory research was executed in which participants EEG activity was measured synchronously in

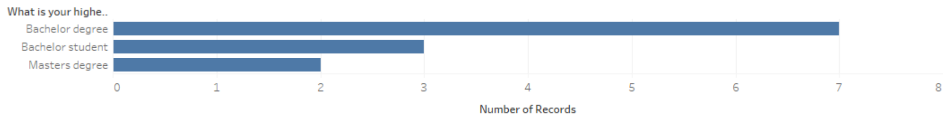


Figure 12: Educational background of the participants

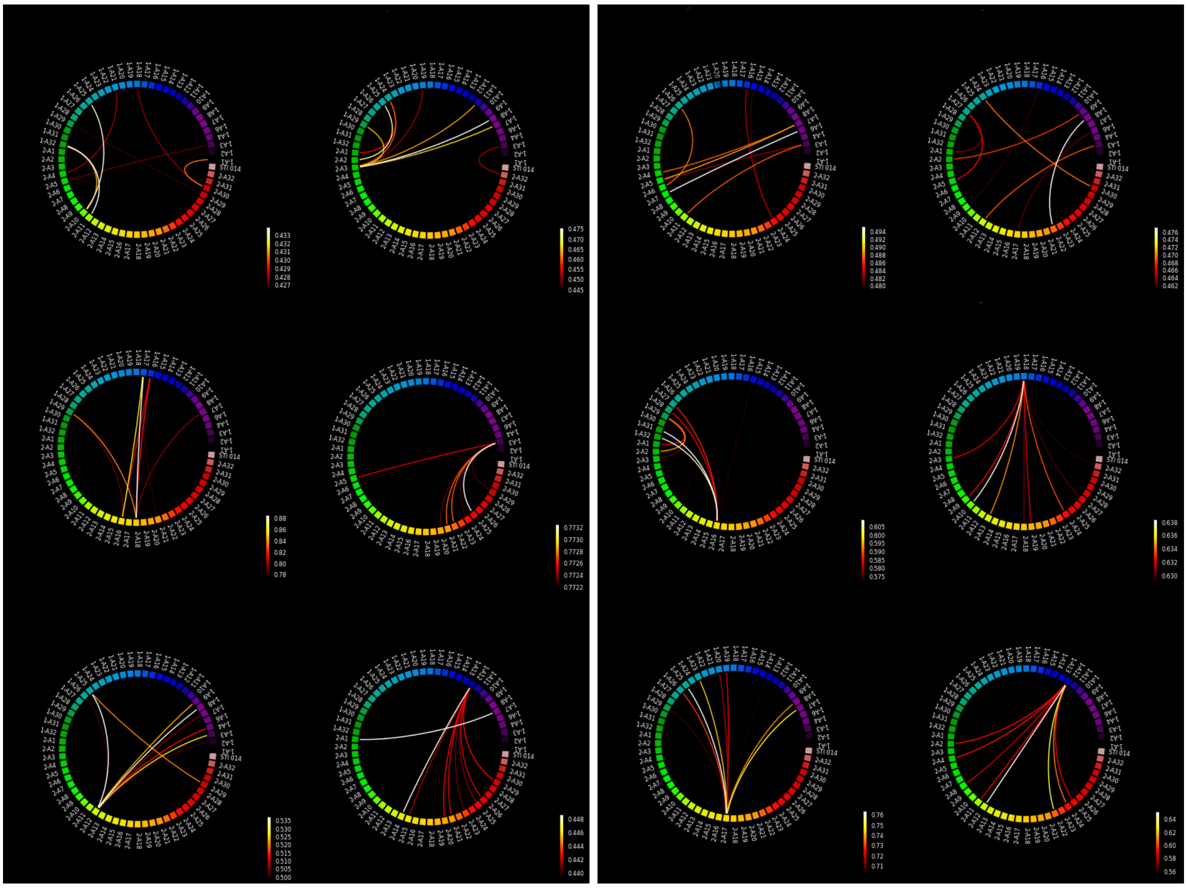
a joint-attention setting (more detail in sect.: 4). The results consist of 2 different measures, with the analyzed EEG recordings on the one side and the outcomes of the SAM questionnaires, that were filled in by the participants in between stimuli, on the other. The main metric on the EEG recordings is the weighter phase lag index (WPLI)(as was described in section 4.4), the results of which are described in section 5.2, followed by a short explanation of how the significance of the results is tested. After that follows a part over outcomes of the SAM questionnaire in section 5.3.

5.1 Participants

In this exploratory experiment 6 dyads participated, of these 6 dyads 5 were male female constellations while one was female female. The 6 dyads were evenly split over the condition couples and strangers. The 12 participants were within the age range between 21 and 29 years old (mean=24) and all had a background in higher education (either current students or recent graduates, see figure 12 for more detail). In two of the dyads one of the participants was left-handed, all other participants were right-handed.

5.2 WPLI

In order to find connectivity (/synchronization) patterns between subjects the ”weighted phase lag index” (WPLI) [Vinck et al., 2011] (using Fast Fourier Transformation (FFT) with a Hanning window) is calculated for all (32*32) possible connections both averaged across the whole frequency range as well as separated per frequency band (see table 1). Weighted PLI is a metric that calculates the synchronity of two signals for a given frequency and within a time window. The signal is transformed into the time-frequency domain using Fast Fourier Transformations (FFT) and then split into time windows using a shifting Hanning-window. This returns a value between 0 and 1 for the amount of synchronization between the 2 signals, where 0 means that two signals do not have a common phase and 1 means that both signals are fully synchronous.



(a) stimulus condition *(b)* rest condition

Figure 13: WPLI plotted between electrodes. On the left side plots from 3 different couple dyads and on the right side 3 stranger dyads, averaged over the range of 1-49 Hz under Stimulus condition (a) and under rest condition (b)

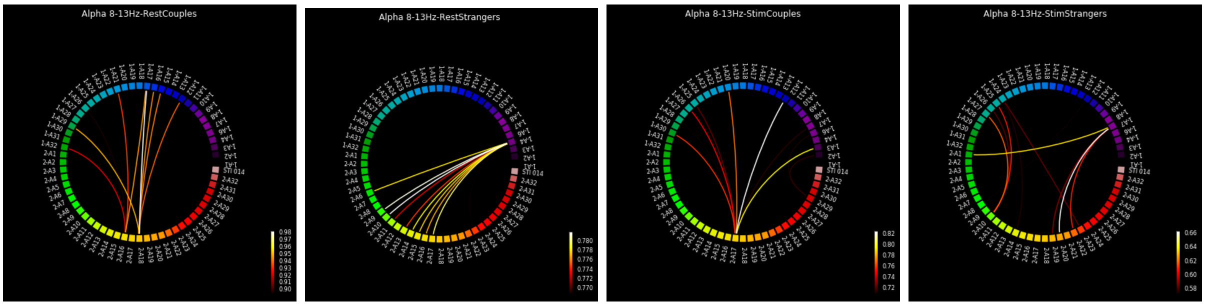
5.2.1 Alpha range

In the alpha frequency band (8-13Hz) the connectivity plots show a pattern that is distinguishable by the naked eye between the groups. There generally tends to be a cluster of strong connections between the participants within the dyad, connecting the parieto-occipital regions for both participants with one another (see figure: 14). When testing the differences with a permutation test[16] [Maris and Oostenveld, 2007] the null-hypothesis could be rejected under rest condition for 2 clusters (.8 CI).

[16] more information about the exact test can be found here: `http://martinos.org/mne/stable/generated/mne.stats.permutation_cluster_test.html`

Table 1: Division of frequency bands

Band	Frequency
Delta	1-4 Hz
Theta	4-8 Hz
Alpha	8-13 Hz
Beta	13-30 Hz
Gamma	30-49 Hz



(a) rest, couples *(b)* rest, strangers *(c)* Stimulated, Couples *(d)* Stimulated, Strangers

Figure 14: WPLI in the alpha range plotted between electrodes. On the left side plots averaged over the couple dyads (under rest condition (a) and Stimulus condition (c)) and on the right side over the stranger dyads(rest condition (b) and stimulus condition (d))

5.2.2 Beta range

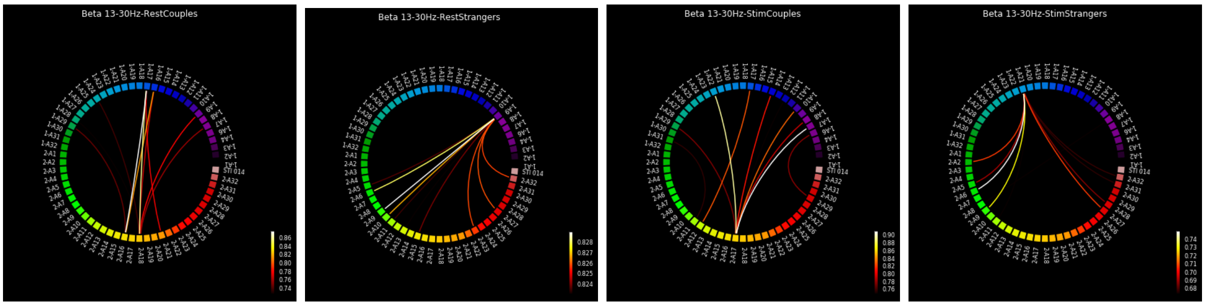
In the beta range (13-30Hz), similar trends as were observed in the alpha band, seem to be present under rest condition during visual analysis (see figure: 15), however, when testing these in the permutation test, they were insignificant ($p \simeq .28$).

5.2.3 Gamma range

In the gamma range (30-49Hz) there seems to be a connectivity present between the right parieto occipital region with the fronto parietal region on the other member of the couple (see figure: 16). This connection is however only present in one direction and does not show up as significant in the permutation test.

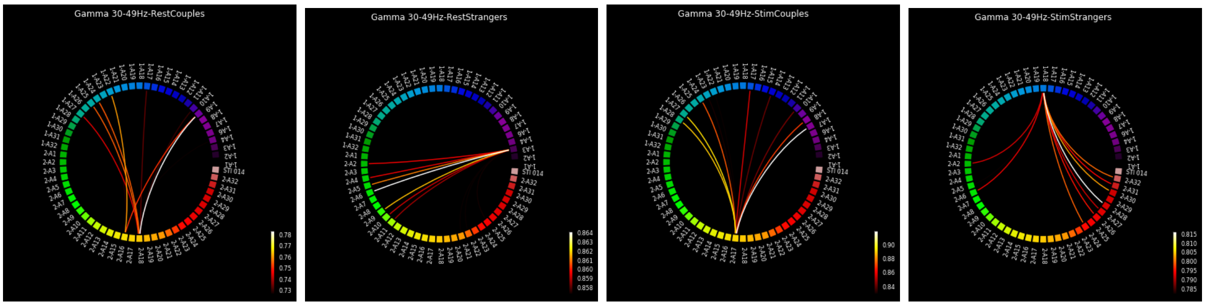
5.2.4 Delta range

In the delta range (1-4Hz), the connection between the right parietal regions are visible for both couples and strangers under rest condition (see figure: 17). This connectivity pattern is therefore not suitable to distinguish the conditions. Under



(a) rest, couples *(b)* rest, strangers *(c)* Stimulated, Couples *(d)* Stimulated, Strangers

Figure 15: WPLI in the beta range plotted between electrodes. On the left side plots averaged over the couple dyads (under rest condition (a) and Stimulus condition (c)) and on the right side over the stranger dyads(rest condition (b) and stimulus condition (d))



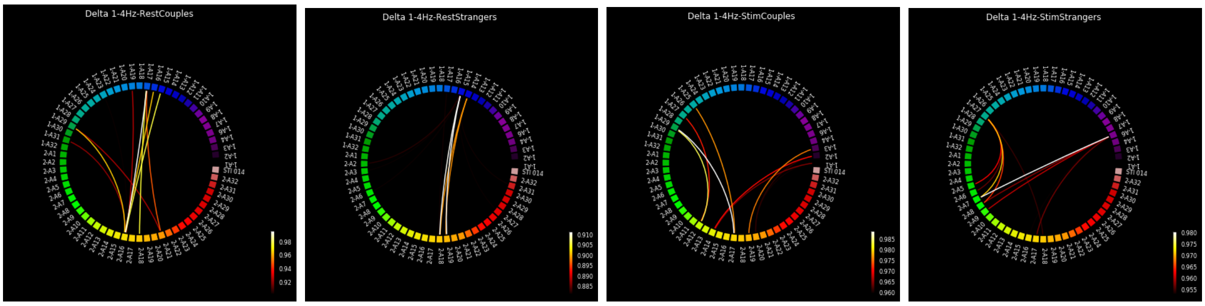
(a) rest, couples *(b)* rest, strangers *(c)* Stimulated, Couples *(d)* Stimulated, Strangers

Figure 16: WPLI in the gamma range plotted between electrodes. On the left side plots averaged over the couple dyads (under rest condition (a) and Stimulus condition (c)) and on the right side over the stranger dyads(rest condition (b) and stimulus condition (d))

stimulus condition there is some connectivity between the central parietal lobe with the anterior frontal lobe for couples, while for strangers there is a connection between the left central and the left temporal lobe. This difference is not significant though.

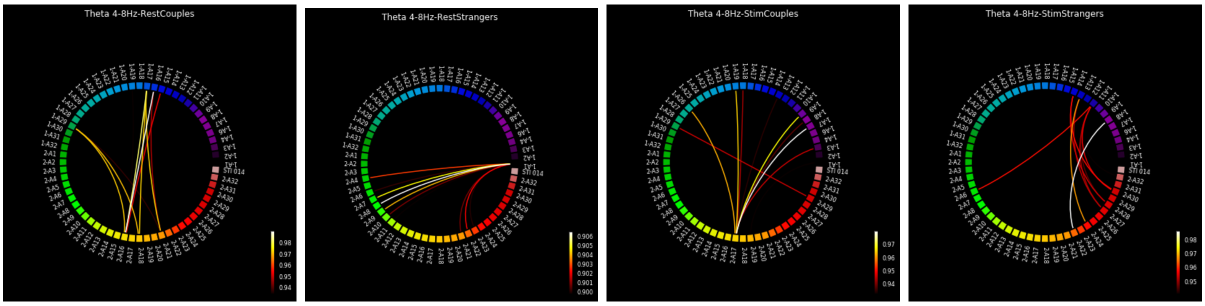
5.2.5 Theta range

In the theta range (4-8Hz) there seems to be a strong connectivity for couples under rest condition between the occipital/parieto-occipital regions that does not seem to be present for strangers (see figure: 18). This difference also comes back significant on the permutation test (.8 CI).



(a) rest, couples *(b)* rest, strangers *(c)* Stimulated, Couples *(d)* Stimulated, Strangers

Figure 17: WPLI in the delta range plotted between electrodes. On the left side plots averaged over the couple dyads (under rest condition (a) and Stimulus condition (c)) and on the right side over the stranger dyads(rest condition (b) and stimulus condition (d))



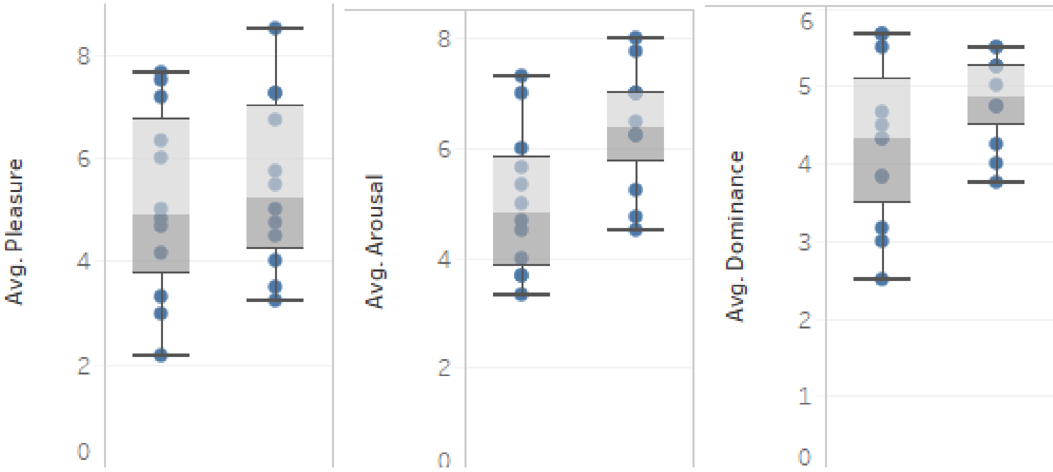
(a) rest, couples *(b)* rest, strangers *(c)* Stimulated, Couples *(d)* Stimulated, Strangers

Figure 18: WPLI in the Theta range plotted between electrodes. On the left side plots averaged over the couple dyads (under rest condition (a) and Stimulus condition (c)) and on the right side over the stranger dyads(rest condition (b) and stimulus condition (d))

5.3 SAM questionnaire

As a test metric to see how similar the couples actually react to the stimuli, each stimulus was tested with a SAM test after the video, by comparing similarities within the dyads between the variables.

From visual inspection it already becomes obvious that there does not seem to be a noticeable difference between the reactions of couples with the reactions of strangers (see figure: 19 and 20). In order to compare the results of the SAM test with the intended reaction of each stimulus, the scores of each participant were translated from the PAD domain to the PANAS scale (Positive Affect - negative affect scale, as developed by [Watson and Tellegen, 1985], which is an almost identical scale, other than it being rotated 45 degrees) in which the stimuli were encoded and then calculating the dot product between the two vectors. The spread between lover



(a) pleasure *(b)* arousal *(c)* dominance

Figure 19: Pleasure (a), Arousal (b) and Dominance(c) results of the SAM test, left graphs show stranger condition, right graph shows couples

and stranger dyads is very similar (as can be seen in figure: 21).

6 Discussion

Coming back to the original Research question that this project set out to answer, which was, whether there are differences observable from EEG signals between couples and strangers in this joint attention setting and the follow-up question whether it is then possible to train a classifier on distinguishing this automatically. It can be concluded that there seem to be neural correlates for social relationships, which are indicated by the null hypothesis getting rejected for some connections both within the alpha range as well as the theta range. However, from the number of participants and especially the number of similar epochs within this experiment, the correlates found in this exploratory research are not yet strong enough to train a reliable classifier on the available data.

A possible explanation for the fact that the differences were found more prominently in the non-stimulus periods might be explainable by the fact that there are more epochs available during which no stimulation took place and that these epochs are more similar to each other (same length, exactly same (non) stimulus, whereas the video of the stimulus phase was different each time.

Another factor that could influence the outcome is the fact that the stimuli are currently biased slightly towards negative emotions (anger/sadness), with some comedic sequences sprinkled in, yet, due to availability, no representatives of other positive emotions, that might be more prown to deliver measures for the emotional

Figure 20: detail responses to each stimulus between couples and strangers including std. dev (grey shadow)

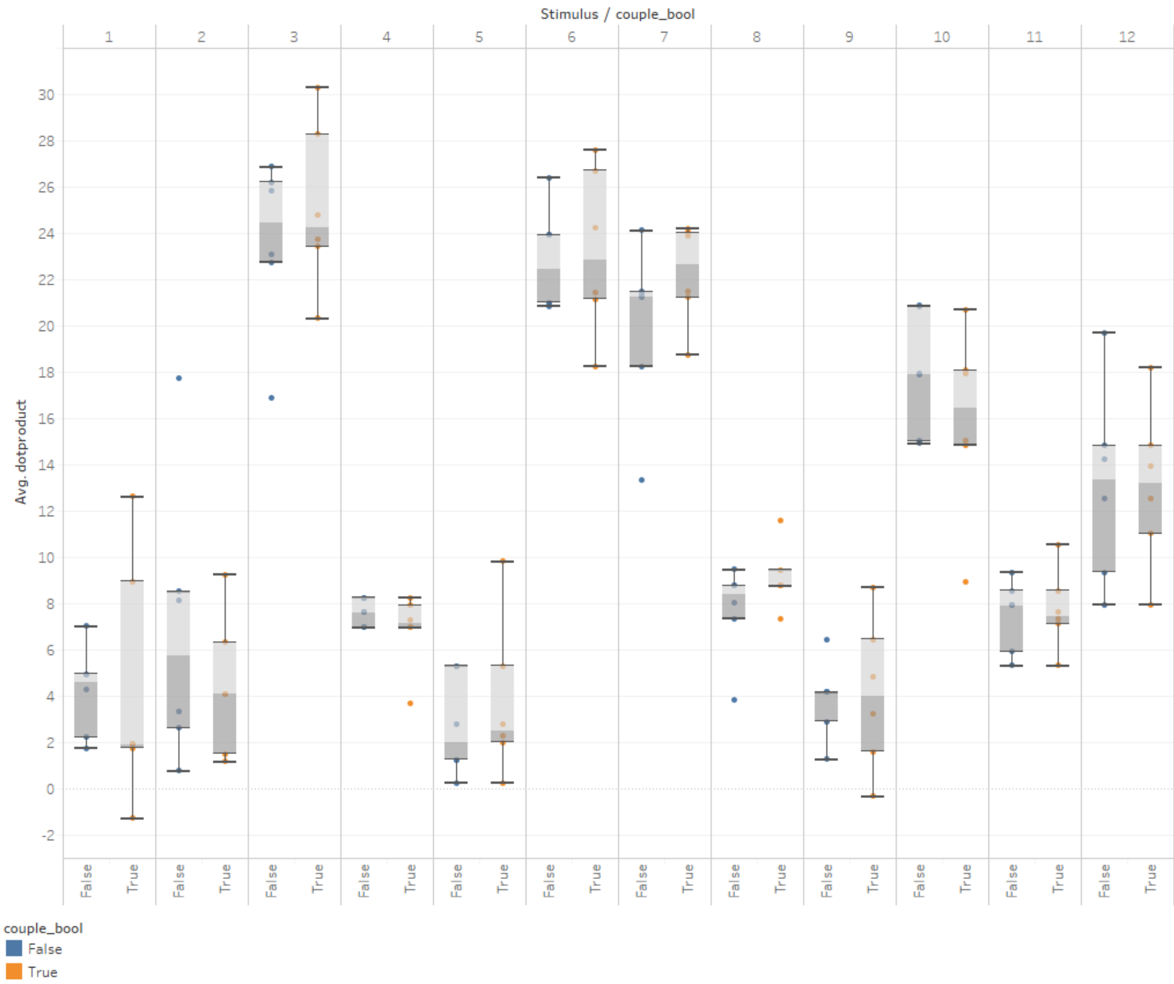


Figure 21: Whisker plot of the commonality between the supposed affect of the stimulus and the actual reaction of the participant

connection of the participants, such as love/romance scenes or hopeful ”happy end” settings.

The differences during the non stimulation phase hint at actual existing differences, it should be investigated whether synchronizations increase in settings with more active social interaction, for example by having blocks of different forms of interactions in the same experiment and then investigating the differences between these.

When comparing the results of this research with those of other experiments, a distinguishing factor seems to be that in most cases active cooperation was required from the participants rather than passive consumption, this could be an indication that these synchronizations take place within the areas responsible for active social cooperation rather than the one's aimed at passive observation.

7 Conclusion & Recommendations

This project explored the possibility of detecting/predicting the social relation, in this experiment this is simplified to the labels strangers and couples, based on EEG hyperscanning recordings in a joint attention setting. Overall, differences were found in non-stimulus situations in the Alpha and Theta range.

7.1 Reflection and Recommendations

During the data analysis phase of this project, several valuable lessons about experiment design were learned that could lead to stronger results when done differently. The low number of epochs in this experiment and especially the sparseness of epochs in which the same emotional response was being evoked lead to the connectivity calculation not being able to correlate as effectively as it otherwise may have. This was not helped by the fact that epochs all had different lengths. Both of these issues stem from the decision to take movie snippets from a standardized library in which the availability of movie sequences was rather limited and that movie scenes develops in different speeds, thus comparing the reaction to different kinds of stimuli which could introduce to additional coherence errors.

It might be advisable to first get a better grip on the underlying neural cause by performing experiments with different kinds of stimuli, allowing for a higher epoch density as well as a stable epoch length that is the same across all conditions.

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A Experiment setup

A.1 Materials

- 3 screens, 1 needs to be at least 24” (presentation), the others can be smaller
- 2 computers, one laptop to play the videos, one desktop pc to control both BioSemi
- 2 BioSemi EEG'S + headcaps
- 1 BioSemi Fibre to USB converter box
- 2 fibre optic channel cables, one to connect the EEGs to each other, one to connect to the PC
- electrolyte gel
- towels

- toothbrush
- shampoo
- consent forms
- pens
- general questionnaire, opened on laptop
- SAM tests on paper (24 tests per experiment)

A.2 Protocol

1. greet both participants
2. offer coffee, tea, etc. for waiting/setup time
3. explain experiment, offer consent form
4. reinforce that stimuli contain shocking sequences
5. give participant time to read/sign/ask questions
6. preliminary tests, questionnaires
7. check: bathroom break?
8. measure head, choose cap
9. place cap on head of participant
10. connect all electrodes using electrolyte gel
11. test signal quality in ActiView, reapply gel/reconnect electrodes where necessary
12. eye tasks for noise correction, blink/roll eyes, play around with mimic for facial responses
13. instruct participants to try and not move during blocks and blink as little as possible during stimuli, try and keep it in between stimuli
14. inform participants that after every stimulus, the presentation stops for a moment so they can fill in SAM test shortly
15. instruct participants to be aware of their emotions and to try and feel with the movie

16. start EEG recording in ActiView
17. start stimulus presentation in OpenSesame
18. follow stimulus presentation step-by-step
19. after end of presentation:
20. remove cap from each participant
21. offer participants cookies
22. if necessary: lead participants the way to a place they can wash their hair, hand out towels
23. thank participants for their effort, offer to keep them informed about the outcomes of the research
24. file results of the SAM sheets under the participant number (no date, no name)
25. file consent forms separately from SAM sheets, making sure the participant number isn't mentioned on the consent form
26. save .bdf file under experiment number (naming scheme: [experiment number][device number] e.g. participant 12 -¿ experiment 1, device 2)
27. transfer .bdf file via USB stick to protected folder on experiment leader's laptop

A.3 Stimuli

For more information about the stimuli used, refer to table 2 or the spreadsheet in the additional information.

Table 2: Stimuli blocks

Movie name	scene description	primary emotion
There is something about Mary	Mary takes sperm from Teds hair mistaking it for hair gel.	Amusement
Life is beautiful	In a prison camp, a father and a boy talk to the mother using a loud speaker	Tenderness
Schindler's list	A concentration camp commander randomly shoots prisoners from his balcony.	Anger
Blue	A woman goes up on an escalator, carrying a box.	Neutral
When Harry met Sally	Sally simulates an orgasm in a restaurant	Amusement
Schindler's list	Killing of jews in a ghetto during WWII	Anger
A perfect World	Butch is gunned down, at the end of the movie.	Sadness
Blue	A person passes a piece of aluminum foil through the window of a car.	Neutral
A fish called Wanda	One of the characters is found naked by the owners of the house	Amusement
Se7en	Policemen find the body of a savagely tortured man	Fear
Blue	a woman arrives walking in an alley. She greets another woman and continues walking.	Neutral
E.T.	E.T. is apparently dying	Sadness

B Participant Information

Informed Consent form for Participation in a Research Study University of Twente

EEG hyperscanning based analysis of neural correlates for social relationships

Description of the research and your participation

You are invited to participate in a research study conducted by Dominik Lenz. The purpose of this research is investigating the neural basis for social relations and how they differ between couples and strangers.

For this purpose your brain activity will be measured by means of Electroencephalography (EEG) throughout the experiment. The preparations for this measurement take up approximately 1 hour before the actual experiment can start. Your participation will involve preparations for the EEG measurement, 40 minutes of stimuli, a short questionnaire and cleaning up afterwards. Your total time investment will be around 2-2.5 hours.

Risks and discomforts

There are no known risks associated with this research, however, the circumstances of EEG measurements may cause some discomfort, as conductive electrolyte gel has to be used on the hair to improve signal quality. A possibility to wash the hair after the experiment will be available.

The video stimuli used in this experiment contain scenes that for some users can be shocking or upsetting.

Potential benefits

There are no known benefits to you that would result from your participation in this research.

Protection of confidentiality

We will do everything we can to protect your privacy. All data is saved only in anonymous form. Your identity will not be revealed in any publication resulting from this study.

Voluntary participation

Your participation in this research study is voluntary. You may choose not to participate and you may withdraw your consent to participate at any time. You will not be penalized in any way should you decide not to participate or to withdraw from this study.

Contact information

If you have any questions or concerns about this study or if any problems arise, please contact Dominik Lenz at d.lenz@student.utwente.nl or the supervising researcher dr. Mannes Poel, m.poel@utwente.nl.

For queries, complaints or comments about the research you can also reach the Faculty of EEMCS Ethical committee through Jorien van Loon, Secretary Ethical Committee EWI, j.vanloon@utwente.nl

Please check the boxes (x)	
1. I have read the explanation and I understand that I can ask questions at any time during the experiment.	
2. I understand that I can quit at any time, without having to give a reason, and that my data then will not be part of the dataset.	
3. I give permission for my data to be used for academic purposes and I am aware that it is anonymous.	

________________________ ____________

Participant's signature Date

________________________ ____________

Researcher's signature Date

C Workflow .BDF to Python

As it proved more difficult than necessary/expected to use the measurement data (and here specifically the event-information) in the data analysis the necessary steps for the transformation are quickly outlined here. Please note that this work flow is the result of trial and error based hacking and as such does at no point claim to be a recommended best practice, but provides a manageable workaround

1. first the .bdf file (BioSemi Data format) is loaded into EDF Viewer[17] and the Events exported as .csv

2. the .csv file is then edited in Notepad++[18] to include "derived" events e.g. always 15s after the stimulus onset event the rest time before the stimulus ends, this event marker is however not sent by the stimulus software directly due to a lack of administrator privileges on the experiment computer -Hint: event names should only be integers, else the MNE library will regularly produce errors, even though EEGLAB handles it without any issue

3. the .bdf is then imported into EEGLAB and combined with the edited event file (text annotation loader)

4. while in EEGLAB, the ICA tool provided in EEGLab is used already and the result saved as a .set file

5. the .set file can then be loaded into MNE using the function:

   ```
   raw= mne.io.read_raw_eeglab("filename")
   events= mne.find_events(raw)
   ```

6. now you're free to use the data in Python

[17] available open source under: https://www.teuniz.net/edfbrowser/
[18] available under GPL license: https://notepad-plus-plus.org