Towards Successful Multi-user Brain-Computer Interface (BCI) Gaming: Analysis of the EEG Signatures and Connectivity

Finda D. Putri, Hao Ding, Abdullah Garcia and Aleksandra Vuckovic
Center of Rehabilitation Engineering, University of Glasgow, Glasgow, U.K.

Keywords: EEG-based BCI, Multi-user BCI, BCI Gaming, Competitive Gaming, Social Interaction.

Abstract: The information related to the impact of multi-user BCI on cortical activity is still relatively limited. This ongoing study performed a competitive multi-user BCI gaming that is based on alpha band operant conditioning and explored the brain activity and connectivity during the most, and the least successful gaming runs. Ten healthy adults were involved in three days of gaming experiments in pairs. Multi-channel paired t-test found a significant decrease ($p<0.05$) of absolute alpha power in the frontal left hemisphere channels in the dominant players during the most successful gaming compared to the baseline of the same group. This decrease is associated with the frontal alpha asymmetry (FAA) that occurred in the leading players. Connectivity estimation via partial directed coherence (PDC) was also performed, showing the deactivation of brain networks during the successful gaming of the dominant players compared to their baseline which might indicate the "networks switching" mechanism from resting state to a more-demanding cognitive task. Different baseline connectivity patterns were also found in the group of dominant players compared to the group of non-dominant players, suggesting the possibility of using baseline connectivity information as a predictor of gaming performance.

1 INTRODUCTION

The development of BCI technology has increased the interest of BCI application for entertainment purpose, commonly formed as BCI games. Gaming is a highly stimulating activity that induces different kinds of cognitive responses, making it very challenging, yet very appealing for BCI application.

More advanced BCI-gaming technology initiated the emerging of multi-user BCI games. The general requirement of a multi-user BCI has been described as the involvement of two or more users with integrated brain activity to a BCI application (Nijholt, 2015; Nijholt & Gürkök, 2013). Social interaction tasks (i.e. cooperation and competition) are ideally implemented in multi-user BCI paradigms (Bonnet, Lotte & Lécuyer, 2013; Gürkök et al., 2013; Nijholt & Gürkök, 2013), as it has been widely used in the classic video gaming.

Multi-user BCI development is a complex process. Several factors composed of technical challenges like the BCI architecture design and the classification accuracy to behavioral factors like the effect of social interaction on BCI performance require special attention. Multiple studies around interactive multi-player BCI gaming have been performed, mainly to test the BCI classification accuracy using different types of control, e.g. Steady-State Evoked Potential (SSVEP) (Cruz et al., 2017; Gürkök et al., 2013), P300 (Korczowski et al., 2016; Korczowski, Congedo & Jutten, 2015), motor imagery (MI) (Bonnet et al., 2013), and the combination of different paradigms such as SSVEP/ P300 with alpha power (Mühl et al., 2009). Some of these studies have also reported the impact of gaming interaction on the quality of BCI performance. For example, Bonnet et al. using BrainArena, an MI-based multi-user BCI game, which was presented as a simple ball game, found that social interaction is not necessarily compensating the quality of BCI performance. Additionally, compared to the single player setup, they reported that the users prefer multi-player gaming due to the fun and motivational factors (Bonnet et al., 2013).

However, contradicting results were found by another study that investigated the different types of game control (BCI control and classic mouse control) and their implications on co-experience during a collaborative BCI game called "Mind The Sheep!" (Gürkök et al., 2013). They found that when using BCI control, co-experience was reduced by

Putri, F., Ding, H., Garcia, A. and Vuckovic, A.
Towards Successful Multi-user Brain-Computer Interface (BCI) Gaming: Analysis of the EEG Signatures and Connectivity.
DOI: 10.5220/0008201400590065
In *Proceedings of the 3rd International Conference on Computer-Human Interaction Research and Applications (CHIRA 2019)*, pages 59-65
ISBN: 978-989-758-376-6

collaborative interaction due to the users' concern of losing control if they were paying too much attention to collaboration.

In the field of multi-user BCI gaming, the amount of information related to the neurological impact of social interaction is still relatively limited. A study by Toppi et al. has explored the cortical changes and effective connectivity in the brain of pairs of pilots during a flight scenario inside the flight simulator (Toppi et al., 2016). They found that in theta band (3-7 Hz), there is a significant influence ($p<0.05$) between the flight phase factor (take-off, cruising, and landing) on connections' density and efficiency, and the involvement of frontal networks of all the pilots. They also reported a significant increase ($p<0.05$) of theta power in the frontal and parieto-occipital areas of the co-pilots during take-off, and in the frontal area of both pilots during landing. A significant increase of parietal alpha power was also found only in co-pilots during landing (the captain led take-off and the co-pilot led the landing due to a deliberate electrical failure applied to the captain's instrumentation). Although physical control was applied instead of BCI control, this study has successfully demonstrated the impact of interaction and the role changes on the cortical activity during a cooperative task that requires a high-degree of concentration, which can be a useful reference for interactive BCI gaming development, especially when applying high concentration task.

The aim of the current study is to analyse the electrophysiological changes of the brain during a competitive multi-user BCI gaming that is based on the alpha band, non-verbalised operant conditioning. We analysed the cortical changes by measuring relative alpha power during gaming and resting states. Neuronal connectivity was estimated in both gaming and resting states, specifically during the most and least successful gaming runs. The following sections of this paper will be organised as: the materials and methods, the results, the discussion, and the conclusion.

2 MATERIALS AND METHODS

2.1 Experimental Setup

Ten healthy able-bodied adults (mean age 26.9±4.14, 6 females and 4 males) participated in EEG experiments where they were sorted into five pairs. They signed the written consent form prior to the experiments. Ethical permission was granted by the University's College Ethical Committee.

The application consisted of three main components: MATLAB functions (MATLAB 2015a, The Mathworks, Inc., USA), a Simulink model and a JAVA (version 1.8.0) Graphical User Interface (GUI). MATLAB worked as an entrance system for the application and served as the connector and controller of the Simulink model and JAVA GUI.

The JAVA GUI shown in Figure 1 displays two bars at each side of the screen and a seesaw in between. Each bar represents the fluctuation of the percentage relative alpha power (RA) to the power of wider frequency band of 2-30 Hz, with a moving average window of 0.5 second provided from the electrode Pz in both players. Scoring was achieved when one player managed to increase the power ≥10% than the other to make their side of seesaw tilt down, and hold it for at least 1 second. The bar changes colour from blue to green whenever players gain 1 point. Prior to gaming experiment, baseline RA was measured from each player to set individual thresholds, which were later used to calculate a normalising coefficient (NC). NC was applied to the input signal generated by the player with a higher threshold in the pair. This was done in order to equalise the initial conditions. Furthermore, these coefficients were acquired by dividing the RA of the player with the lower threshold (RA_{Low}) by that of the player with the higher threshold (RA_{High}), explained as follows:

$$NC = RA_{Low} / RA_{High} \tag{1}$$

This approach is expected to help the non-dominant player to maintain their control over their bar even if their opponent has significantly higher baseline alpha power.

EEG signal was recorded by a g.USBamp (g.tec medical engineering GmbH., Austria) amplifier. The EEG electrodes arrangement was set following the standardised 10-20 EEG electrode placement system (Homan, Herman & Purdy, 1987). The impedance was kept below 5 kΩ. Linked ear reference was used and FCz was used as the ground. Sampling frequency was set to 256 Hz. Online band-pass filter was set between 0.5 and 60 Hz (and a notch filter at 50 Hz) using 5th order infinite impulse response (IIR) digital Butterworth filter within the g.USBamp.

During the EEG experiments, two players were seated next to each other in front of one screen. They were instructed to compete with each other by increasing the power bar located on their side of the screen and to 'push down' the seesaw such that it would be heavier towards their side.

Each pair performed three experimental sessions on three separate days, where each session consisted of six sub-sessions (5 minutes each). Pre- and post-gaming eyes-open baseline were recorded in a relaxed state for 2 minutes in every session. For the first two sessions, EEG was recorded from only Pz electrode, and for the third session, 32 and 16 electrodes were used by the dominant (D) and the non-dominant (ND) group of players respectively, where the dominance was decided based on the highest average scoring performance in the previous two sessions.

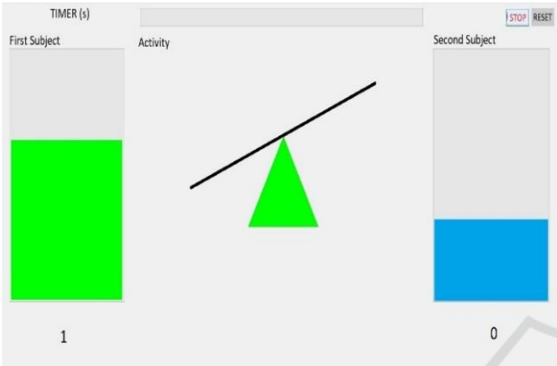

Figure 1: Competitive gaming interface. Users have to increase their power bar ≥10% than the other for at least 1 second to score 1 point.

2.2 Data Analysis

All EEG data were analysed using EEGLAB (UC San Diego, SCCN, USA) toolbox in MATLAB. All EEG data were band-pass filtered between 2 and 30 Hz. For single-channel data, visual inspection and manual noise removal were performed, and for multi-channel data, independent component decomposition was performed by using an Independent Component Analysis (ICA) algorithm implemented in EEGLAB for further noise removal.

The average power spectrum analysis was estimated by using Welch's method (Welch, 1967), with a 50% overlap of 4 second long windows. Individual RA at Pz was analysed at a group and individual level. Spatial distribution of power in all conditions was estimated based on multi-channel EEG recording. Paired t-test analysis was applied to multi-channel EEG data to test statistical significance in absolute power between conditions.

PDC, a multivariate measurement of directional causality in the frequency domain, was calculated to estimate brain connectivity. PDC from *i* to *j* can be defined as:

$$\pi_{ij}(f) = \frac{\overline{A}_{ij}(f)}{\sqrt{a_j^*(f)a_j(f)}} \qquad (2)$$

Where $\overline{A}_{ij}(f)$ is the *i*,*j*-th element of A(*f*), a matrix of frequency domain transformed model coefficient, and $a_j(f)$ is the *j*-th column of matrix A(*f*) (Baccalá & Sameshima, 2001). PDC values were measured from 10 representative electrodes and the significant PDC values were estimated by using asymptotic statistic ($p < 0.05$) and False Discovery Rate (FDR) correction ($p < 0.05$) was applied for multiple comparisons.

3 RESULTS

Scoring results were used to measure the BCI performance of the users. From all three sessions (in a total of 30 gaming sub-sessions per session for all 5 pairs), on average, group D won all the time in the first and second session and won only 80% (24 sub-sessions) in the third session (group ND won 6 sub-sessions). Results in Figure 2 show the average percentage of individual gaming RA along with the average scoring performance, from all sessions. The bars with an asterisk represent the players with higher baseline RA, where NC was applied to their RA during gaming (these players received feedback of their normalised RA instead of their real RA). Our results suggest that higher baseline RA does not always reflect better performance. Players with lower baseline RA can still win the game. It also shows that daily adjustment of the baseline RA was necessary, as in some pairs, different players had larger/smaller baseline RA on different days.

In multi-channel data, two gaming conditions were selected based on the highest/lowest scores of the last session. Table 1 shows the scores of the highest and the lowest scoring gaming sub-sessions in both groups during the last experimental session. Based on this measure, the multi-channel analysis was grouped into the highest scoring D, lowest scoring D, highest scoring ND, and lowest scoring ND. We then categorised highest scoring D as "the most successful gaming" and the lowest scoring ND as "the least successful gaming".

Paired t-test ($p<0.05$) of the multi-channel data across subjects (FDR correction applied) found significant decrease of absolute alpha power only in the most successful gaming compared to their baseline, specifically in the frontal electrodes of the left hemisphere (FP1, AF3, FC5, and FC3), as seen in Figure 3. There is no statistical significance found in the theta and beta bands in all conditions and groups, showing the selectivity of EEG power modulation in the alpha band only. Although there is no significant increase found on the training electrode, Figure 3 shows that spatially source of high alpha was reduced around Pz during successful gaming.

Figure 4 shows the estimated PDC in the alpha band, which reflects the connections among networks during baseline of both groups, and during the most successful gaming condition, highest scoring D (red square), and its counterpart- the other player on that particular session, and during the least successful gaming, lowest scoring ND (blue square), and its counterpart. Ten electrodes covering four brain cortical areas were chosen as the representative nodes (i.e., F3, Fz, F4, C3, Cz, C4, P3, Pz, P4 and Oz). Our observations found higher connectivity during baseline in group D (players with higher baseline RA), which are indicated by the higher estimated PDC values and the more complex connected networks, in contrast, the baseline of the group with lower RA (Figure 4 top right) shows relatively lower estimated PDC values and less connected networks.

Table 1: The highest scoring (Hi) and the lowest scoring (Lo) gaming sub-sessions (SS) in both groups.

Pair		**D**		**ND**	
		Hi	Lo	Hi	Lo
1	Score	149	134	6	1
	SS	3	6	5	1
2	Score	114	54	96	38
	SS	2	4	4	2
3	Score	105	76	61	33
	SS	3	5	4	3
4	Score	86	50	72	50
	SS	4	3	5	4
5	Score	139	105	38	17
	SS	3	5	2	1

During the most successful gaming (red square), our results show that the connectivity is decreasing (from baseline state) in terms of the PDC values and the number of network connections, and the remaining networks from baseline are found around the frontal electrodes. The ND counterpart of the most successful gaming shows increased connectivity around frontal and central areas, specifically in the left hemisphere (F3 ↔ Fz and C3 ↔ Cz) with an emerging connection from C3 to P3 compared to their baseline state. Similar to their counterparts, occipital connectivity is decreasing compared to baseline. This ND group is just the counterpart of the most successful gaming, not necessarily depicting the highest scoring condition for the group ND.

For the least successful gaming (blue square), compared to their baseline, the number of connections found are low, with the only strong remaining connection found from F3 to Fz. The D counterpart of the least successful gaming, shows higher PDC values in the parieto-occipital connectivity, compared to their baseline and the highest scoring D. In contrast to the most successful gaming, group D of this particular condition shows more complex connectivity, reflecting that this is not their successful gaming performance, despite still dominating group ND during gaming.

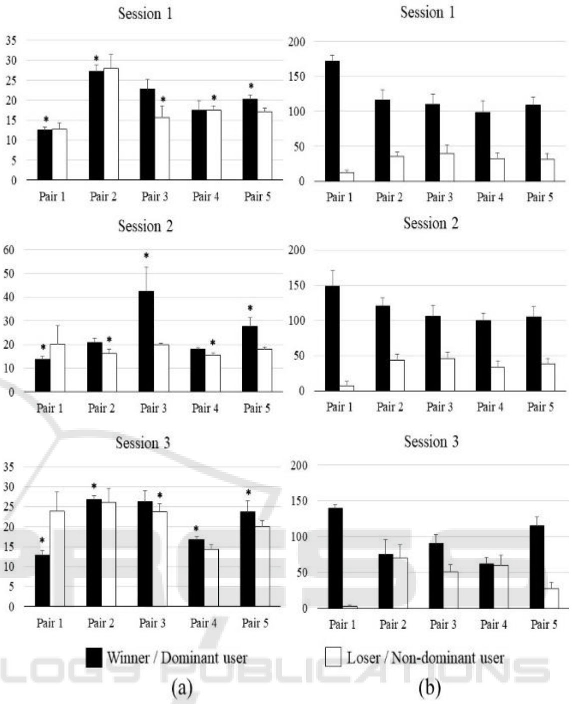

Figure 2: (a) Mean and standard deviation of individual gaming RA (%) at Pz from all sessions. The bars with asterisks show normalised RA, which used as the feedback to the players with higher baseline RA, and the bars without asterisks show real RA. (b) Mean and standard deviation of scores from all users from all sub-sessions.

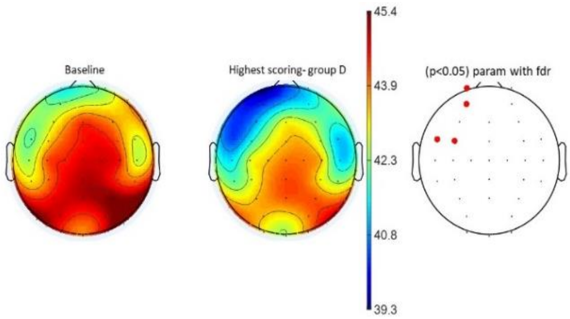

Figure 3: Paired t-test analysis shows a significant decrease of alpha in some frontal electrodes during the highest scoring gaming sub-sessions compared to baseline before gaming for group D.

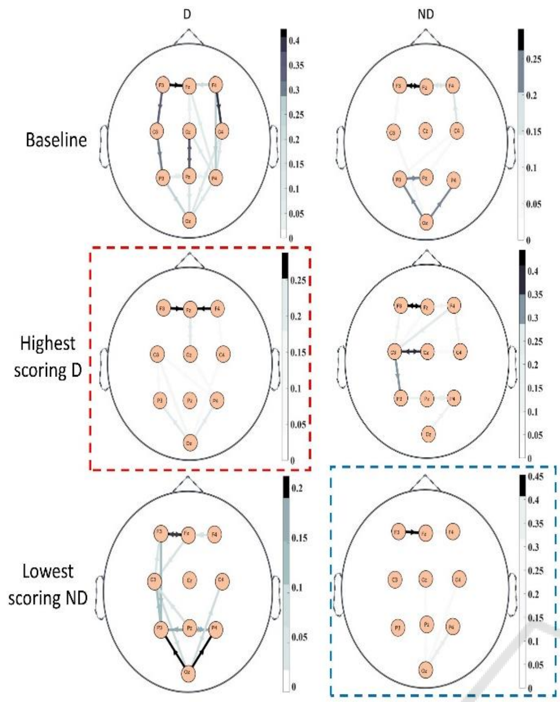

Figure 4: PDC estimation results show connectivity in the alpha band in ten electrodes during baseline (top) and the highest scoring D (red square) and its counterpart representing the most successful gaming (middle), and the lowest scoring ND (blue square) and its counterpart (bottom).

4 DISCUSSION

The present study aimed to examine the effect of competitive gaming on brain cortical activity and neuronal connectivity. The results from the average of the individual gaming RA and the average scoring suggest that higher average RA (both in baseline and during gaming) does not directly produce higher scores. We found a case where the winning player had a lower average RA during gaming. One reason for this is that during gaming, players with higher baseline RA received feedback on normalised, i.e. lower RA than their original RA. In order to score, timing is essential, as someone can only score if they manage to hold their bar higher for at least 1 second. Thus, in this case, the losing player was not able to sustain high alpha power for a relatively long period, though on average, their RA might be high. BCI control requires skill and training is necessary to help the users obtaining and maintaining that skill. In this setup, the players were not only expected just to increase their RA, but also to control its duration and to play based on the opponent's feedback which is changing over time.

Our multi-channel spectral analysis shows a significant decrease of frontal alpha power during the most successful gaming performed by the dominant players. It has been known that naturally, alpha power tends to decrease during task-engagement (Bazanova & Vernon, 2014) and frontal alpha suppression has been reported during interactive synchronized finger-tapping task of two subjects, particularly stronger in the leading subjects, reflecting their higher cognitive investment during the synchronized action (Konvalinka et al., 2014). However, in our results, significant activation only occurred in one side of the hemisphere, indicating that this suppression might be related to the frontal alpha asymmetry (FAA) which is defined as the different frontal alpha activity between hemispheres (Davidson et al., 1990). FAA has been associated with the motivation of approaching and withdrawing behavior, to be specific, if the left hemisphere is more activated, then it is associated with approaching behavior rather than withdrawing behavior (Coan & Allen, 2004), thus our results might reflect the motivation to be engaged in the task by the winning players. Furthermore, left hemisphere activation in a social setting has been associated with unsocial and anti-social behavior (Hecht, 2014), which is in line with our competitive setting, where the players were expected to play against each other.

Connectivity estimation results in the alpha band during successful gaming have demonstrated the connectivity pattern changes, which consisted of the deactivation of several network connections from resting state to gaming performance. Previous observations of the changing connectivity pattern between resting state and cognitive task, have indicated the involvement of three different brain networks such as the default mode network (DMN), the central executive network (CEN), and the salience network (SN) (Goulden et al., 2014; Seeley et al., 2007; Sridharan, Levitin & Menon, 2008). The DMN has been defined as a group of networks which is found to be more active when the task-engagement is absent whereas the CEN is a group of network that is activated when the brain is engaged in a specific mental task (Greicius et al., 2003; Raichle et al., 2001; Seeley et al., 2007). The SN, which comprised of the ventrolateral prefrontal cortex, fronto-insular cortex, and anterior cingulate cortex, is known as the mediator network that helps the network switching between task-free and task-engagement states, between the DMN and the CEN (Goulden et al., 2014). An alpha neurofeedback training was reported increasing the SN connectivity, where this increased connectivity was also found to be negatively correlated with mind-wandering task and resting alpha rhythm (Ros et al., 2013), two conditions which activate the DMN (Neuner et al., 2014; Simon & Engström, 2015).

Our connectivity results also show different connectivity patterns during baseline in different groups. This difference might reflect the possibility of using resting state connectivity to predict gaming performance, where the similar idea has been proposed in predicting the neurofeedback training response in individuals with anxiety (Scheinost et al., 2014).

In order to obtain more detailed connectivity information, especially regarding the pattern changes between the three major networks, more specific and larger number of electrodes should be chosen for connectivity analysis. Larger number of subjects and different range of frequency bands are also required to explore the different impact of interactive BCI gaming in different frequency bands. An equal number of electrodes for both players should be used for the last gaming session to avoid bias by the more/less dominant players.

5 CONCLUSIONS

Our study introduced a multi-user competitive BCI game that is based on alpha operant conditioning. We reported the preliminary results of the cortical changes and connectivity from the most successful gaming. Further development of this study will include more participants and other social interaction settings (i.e., collaborative), in order to explore the brain activity and connectivity during the different interaction tasks.

ACKNOWLEDGEMENTS

This study is funded by Indonesian Endowment Fund for Education by the Ministry of Finance, Republic of Indonesia.

REFERENCES

Baccalá, L. A., & Sameshima, K. J. B. c. (2001). Partial directed coherence: a new concept in neural structure determination. *84*(6), 463-474.

Bazanova, O., & Vernon, D. (2014). Interpreting EEG alpha activity. *Neuroscience & Biobehavioral Reviews, 44*, 94-110.

Bonnet, L., Lotte, F., & Lécuyer, A. (2013). Two brains, one game: design and evaluation of a multiuser BCI video game based on motor imagery. *IEEE Transactions on Computational Intelligence, 5*(2), 185-198.

Coan, J. A., & Allen, J. J. (2004). Frontal EEG asymmetry as a moderator and mediator of emotion. *Biological psychology, 67*(1-2), 7-50.

Cruz, I., Moreira, C., Poel, M., Ferreira, H., & Nijholt, A. (2017). *Kessel Run-A Cooperative Multiplayer SSVEP BCI Game.* Paper presented at the International Conference on Intelligent Technologies for Interactive Entertainment.

Davidson, R. J., Ekman, P., Saron, C. D., Senulis, J. A., & Friesen, W. V. (1990). Approach-withdrawal and cerebral asymmetry: emotional expression and brain physiology: I. *Journal of Personality Social Psychology, 58*(2), 330.

Goulden, N., Khusnulina, A., Davis, N. J., Bracewell, R. M., Bokde, A. L., McNulty, J. P., & Mullins, P. G. (2014). The salience network is responsible for switching between the default mode network and the central executive network: replication from DCM. *Neuroimage, 99*, 180-190.

Greicius, M. D., Krasnow, B., Reiss, A. L., & Menon, V. (2003). Functional connectivity in the resting brain: a network analysis of the default mode hypothesis. *Proceedings of the National Academy of Sciences, 100*(1), 253-258.

Gürkök, H., Nijholt, A., Poel, M., & Obbink, M. (2013). Evaluating a multi-player brain–computer interface game: Challenge versus co-experience. *Entertainment Computing, 4*(3), 195-203.

Hecht, D. (2014). Cerebral lateralization of pro-and anti-social tendencies. *Experimental Neurobiology, 23*(1), 1-27.

Homan, R. W., Herman, J., & Purdy, P. (1987). Cerebral location of international 10-20 system electrode placement. *Electroencephalogr Clin Neurophysiol, 66*(4), 376-382.

Konvalinka, I., Bauer, M., Stahlhut, C., Hansen, L. K., Roepstorff, A., & Frith, C. D. (2014). Frontal alpha oscillations distinguish leaders from followers: multivariate decoding of mutually interacting brains. *Neuroimage, 94*, 79-88.

Korczowski, L., Barachant, A., Andreev, A., Jutten, C., & Congedo, M. (2016). *" Brain Invaders 2": an open source Plug & Play multi-user BCI videogame.* Paper presented at the 6th International Brain-Computer Interface Meeting (BCI Meeting 2016).

Korczowski, L., Congedo, M., & Jutten, C. (2015). *Single-trial classification of multi-user P300-based Brain-Computer Interface using riemannian geometry.* Paper presented at the 2015 37th annual international conference of the IEEE engineering in medicine and biology society (EMBC).

Mühl, C., Gürkök, H., Bos, D. P.-O., Thurlings, M. E., Scherffig, L., Duvinage, M., . . . Heylen, D. (2009). *Bacteria Hunt: A multimodal, multiparadigm BCI game*. Paper presented at the Fifth International Summer Workshop on Multimodal Interfaces.

Neuner, I., Arrubla, J., Werner, C. J., Hitz, K., Boers, F., Kawohl, W., & Shah, N. J. (2014). The default mode network and EEG regional spectral power: a simultaneous fMRI-EEG study. *PLoS One, 9*(2), e88214.

Nijholt, A. (2015). Competing and collaborating brains: multi-brain computer interfacing. In *Brain-Computer Interfaces* (pp. 313-335): Springer.

Nijholt, A., & Gürkök, H. (2013). *Multi-brain games: cooperation and competition*. Paper presented at the International Conference on Universal Access in Human-Computer Interaction.

Raichle, M. E., MacLeod, A. M., Snyder, A. Z., Powers, W. J., Gusnard, D. A., & Shulman, G. L. (2001). A default mode of brain function. *Proceedings of the National Academy of Sciences, 98*(2), 676-682.

Ros, T., Théberge, J., Frewen, P. A., Kluetsch, R., Densmore, M., Calhoun, V. D., & Lanius, R. A. (2013). Mind over chatter: plastic up-regulation of the fMRI salience network directly after EEG neurofeedback. *Neuroimage, 65*, 324-335.

Scheinost, D., Stoica, T., Wasylink, S., Gruner, P., Saksa, J., Pittenger, C., & Hampson, M. (2014). Resting state functional connectivity predicts neurofeedback response. *Frontiers in Behavioral Neuroscience, 8*, 338.

Seeley, W. W., Menon, V., Schatzberg, A. F., Keller, J., Glover, G. H., Kenna, H., . . . Greicius, M. D. (2007). Dissociable Intrinsic Connectivity Networks for Salience Processing and Executive Control. *Journal of Neuroscience, 27*(9), 2349-2356. doi:10.1523/JNEUROSCI.5587-06.2007 %J The Journal of Neuroscience

Simon, R., & Engström, M. (2015). The default mode network as a biomarker for monitoring the therapeutic effects of meditation. *Frontiers in Psychology, 6*, 776.

Sridharan, D., Levitin, D. J., & Menon, V. (2008). A critical role for the right fronto-insular cortex in switching between central-executive and default-mode networks. *Proceedings of the National Academy of Sciences, 105*(34), 12569-12574.

Toppi, J., Borghini, G., Petti, M., He, E. J., De Giusti, V., He, B., . . . Babiloni, F. (2016). Investigating cooperative behavior in ecological settings: an EEG hyperscanning study. *PLoS One, 11*(4), e0154236.

Welch, P. (1967). The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. *IEEE Transactions on Audio and Electroacoustics, 15*(2), 70-73. doi:10.1109/TAU.1967.1161901