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EEG hyperscanning study of team neurodynamics analysis during cooperative and competitive interaction

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M.Sc. Thesis
July 2019

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Preface

I would like to show my gratitude to the members of my supervising committee, namely, Dr. M.Poel,Dr. N.Thammasan Msc and Prof.Dr.D.K.J.Heylen, for their support and assistance. I also would like to thank Johan de Heer,Paul Porskamp and Rafal Hrynkiewicz, for providing me with the opportunity to undertake this interesting and illuminating study. Moreover, I would like to show my deep gratitude to the subjects who has volunteered to participate in this study, for taking the time to undergo the long experiments. The experience gained will be the building blocks for my career, since it also helped me to cope with different cultures and working style.

Summary

The ’social brain’ has become a central focus of interest in neuroscience research in order to define the neurophysiological basis of social behavior and inter-subjective interactions [1]. Cooperation and competition, in particular, can be considered as a social interaction between two or more agents who intend to facilitate, but also obstruct, others goal achievement [2]. This paper aims to analyze team neurodynamics during cooperative and competitive interactions.

This study set out to analyze team neurodynamics during cooperative and competitive interaction with EEG in four directions: (1) analyzing to what extent are neural synchronization measurements robust to the noise; (2) analyzing team neurodynamics based on different neural synchrony measurements (3) explaining neural synchrony in graph theory (4) relating team neurodynamics with team performance.

18 subjects (9 pairs) participated in the experiment, playing competitive and cooperative computer pong-games in dyads with EEG. Five functional connectivity methods were applied to quantify neural synchronies: intersite phase clustering, phase lag index, spectral coherence, power correlation and mutual information. Team brain networks were generated based on intra- and inter-brain neural synchrony. Topological properties of brain networks, which include small-world-ness, global efficiency and betweenness centrality, were calculated to quantify team neurodynamics.

The results show that: (1) with regard to robust of neural synchrony measurements: mutual information is very sensitive to noise; power-correlation is the least noise-sensitive NS measurement; phase-lag-index can lose some significant neural synchronies; intersite phase clustering and spectral-coherence have similar sensitivity to white noise; (2) Intra-brain neural synchronization shows prefrontal and parastriatel were highly activated on cooperation and competition; (3) Neural synchrony is unstable over frequency and fluctuate dramatically over time; (4) Inter-brain synchrony on cooperation is slightly stronger than interpersonal synchrony on competition; (5) Inter-brain synchrony does not highly correlate with team-performance; (6) Intra-brain network exchange information more efficient than team-brain network; (7) Individual brain exchanges information more efficient on competition as compared with cooperation; (8) Individual brain network has more clusters on cooperation as compared with competition; (9) Team-brain network has more cluster as compared with individual-brain network; (10) Global efficiency and small-world-ness of brain networks are relatively unstable over time and relatively stable over frequency; (11) Small-world-ness of intersite-phase-clustering-based networks has large variance; (12) Brain hubs changes over time; (13) Statistically significant INS between co-operation and competition dynamically changes over time, frequency and among different neural synchrony measurements.

This research has many limitations. As regards the experiment, pong-game can not perfectly imitate cooperation and competition; dyads are acquaintances instead of close friends; experiments were not conducted in a quiet environment; there was no baseline experiment in this research to compare cooperative or competitive scenario as neural patterns may be not elicited by cooperation or competition. With regard to methodologies: only one arbitrary frequency band (beta) was applied in this study instead of multiple frequency bands, while results showed that neural synchrony is unstable over frequency; data were averaged over time while neural synchrony fluctuates dramatically over time; there are many variance definitions of the topological properties (s.t., brain hubs could be measured by betweenness centrality or degree centrality), but this research only applied one definition by time constraint.

In the future work, experiments could be redesigned to better imitate cooperative and competitive interactions. More subjects (close friends) could be recruited with similar age. Results could be analyzed over time or frequency instead of averaging on time and frequency. Baseline experiments could be conducted (in human-to-machine setting or the same game setting without social interaction). Topological properties could be calculated based on different definitions. Multi-layer network could be generated in temporal or frequency domain.

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List of acronyms

EEG	Electroencephalography
FC	Functional Connectivity
SWN	Small-World-Ness
GE	Global Efficiency
MI	Mutual Information
INS	Interpersonal Neural Synchronization
BA	Brodmann Area
ISPC	Intersite Phase Clustering
PLI	Phase-Lag Index
MS	Mentalizing System
MNS	Mirror Neuron Systems
TPJ	Temporal-Parietal Junction
PFC	The Prefrontal Cortex
dmPFC	Dorsomedial Prefrontal Cortex
IFG	Inferior Frontal Gyrus
fMRI	Functional Magnetic Resonance Imaging
MEG	Magnetoencephalography
TMSI	Twente Medical Systems Internation B. V
NS	Neurophysiologic Synchronies
SNR	Signal to Noise Ratio

DLFC Dorsolateral Frontal Cortex

DLPFC The Dorsolateral Prefrontal Cortx

Chapter 1

Introduction

1.1 Context

The 'social brain' has become a central focus of interest in neuroscience research in order to define the neurophysiological basis of social behavior and inter-subjective interactions [1]. When people interact with each other, neurophysiological, perceptual-motor, and cognitive-behavioral patterns emerge between subjects that would not otherwise develop individually [3]. Cooperation and competition, in particular, can be considered as a social interaction between two or more agents who intend to facilitate, but also obstruct, others goal achievement [2]. Cooperation and competition are two common and opposite models of interpersonal exchange [4]. Earlier work investigated how cooperation and competition is influenced by creativity [5] [6], feedback [1] [7] [8] [1] [9] [10] [1] [11] [12] [13] [14] [1], personality [2] [1] [11] [14], emotion [15] [16] and belief [17] and strategies [13] [9] [10] [1] [18].

As for the neural networks involved during cooperative and competitive behaviors, involvement of relevant prefrontal areas has been founded [5] [8] [2] [9] [10] [11] [12] [14] [19]. Particularly, higher The Prefrontal Cortex (PFC) activity was related with post-feedback than pre-feedback [8]; brain activation in The Dorsolateral Prefrontal Cortx (DLPFC) was related with negative feedback [13] [18] [1] [9] [7] and the creative performance [6]. However, although cooperation and competition share some important neural patterns, they do have some differences: Interpersonal Neural Synchronization (INS) increased in the right DLPFC and right Temporal-Parietal Junction (TPJ) only on cooperation [19]; brain activation in Inferior Frontal Gyrus (IFG) reduced/increased during cooperative/competitive interaction [20]; activation in DLPFC is greater on competition [18].

Notably, all previous studies did not apply graph theory to analyze neural dynamics on cooperation and competition. Graph theory, which is a valuable framework to study the organization of functional and anatomical connections in the brain, can offer a different perspective to explain neural patterns. For example, many brain disorders, such as Alzheimer's disease, schizophrenia, autism, attention deficit/hyperactivity disorder and epilepsy, often present abnormalities in brain networks [21]. Topological properties, which can be calculated based on brain networks, also can offer some meaningful explanations in neural patterns. For example, brain hubs are central in brain communication and neural integration [22], brain with attention-deficit disorder exhibit large local efficiency as compared with health brains [23].

A second critical point is that only one synchrony measurements was applied in each previous study. However, different neural methods have different features, therefore, it is interesting to check weather neural patterns are consistent among all different neural synchrony measurements. In this research, neural synchrony is quantified by Functional Connectivity (FC), which is the connectivity between brain regions that share functional properties. More specifically, it is the temporal correlation between spatially remote neurophysiological events, expressed as deviation from statistical independence across these events in distributed neuronal groups and areas [24].

1.2 Problem Statement

The present research therefore intends to extend team neurodynamics analysis with Electroencephalography (EEG) in four directions: (1) To what extent is neural synchrony measurements robust to noise (2) What are intra- and inter-brain neural synchronizations on different functional connectivity methods (3) How to explain neural synchrony in graph theory (4) What is the relationship between team -performance and team neural dynamics

EEG is very sensitive to noise and it is hard to obtain the clean brain signals, therefore the first objective is measuring to what extent are FC methods robust to noise.

As for the second objective, nearly all papers only applied one FC method to quantify Neurophysiologic Synchronies (NS) and draw conclusions without comparing results from other FC methods. However, each FC method has features and assumptions. For example, Mutual Information (MI) can capture nonlinear information while most other methods (s.t. power correlation) are unable to do so. Although Phase-Lag Index (PLI), spectral coherence and Intersite Phase Clustering (ISPC) are all phase-based methods, ISPC measures how phase angle differences cluster, PLI measures weather phase angle difference vectors point to the same direction on the polar plane while spectral coherence weights phase angle differences with power. Therefore, it is interesting to figure out weather neural patterns are consistent among different FC methods. Five FC methods were analyzed in this paper: ISPC, spectral coherence, PLI, power correlation and MI.

In terms of the third objective, network neuroscience successfully detects some cognitive-capacity-related disease (s.t attentiondeficit/hyperactivity disorder [23], schizophrenia [25]) with topological properties. However, so far, very little attention has been paid to explain team neurodynamics in graph theory.

With regard to the fourth objective, although extensive research has linked team performance with INS for cooperation [26] [27] [28] [29] [30] [31], nearly no signal study investigated how team-performance relates with topological properties of the team brain network. This paper analyzed how team-performance relates with INS and Global Efficiency (GE) of the team brain network.

1.3 Paper structure

The remainder of this paper is organized as follows. Chapter2 first gives a brief literature overview of studies about competition and cooperation, introduces two neural systems that are involved in social interaction, and lays out the theoretical dimensions of the research: NS calculation, network formation and topological properties calculation. Chapter3 begins by looking at participants distribution followed by introducing experiment setting-up, procedure and workflow. Chapter.4 presents the findings of the research, focusing on the 6 dimensions: robust of neural synchrony measurements; strong neural synchrony; statistically significant inter-brain neural synchrony; inter-brain synchrony over frequency; relationship between behavioral data and team-performance; topological properties of intra- and team-brain networks. In Chapter5 and Chapter6, discussion and conclusion are given respectively.

Chapter 2

Literature review

2.1 Cooperation/Competition

The 'social brain' has become a central focus of interest in neu- roscience research in order to define the neurophysiological basis of social behavior and inter-subjective interactions [1]. When people interact with each other, neurophysiological, perceptual-motor, and cognitive-behavioral patterns emerge between subjects that would not otherwise develop individually [3]. Cooperation and competition, in particular, can be considered as a social interaction between two or more agents who intend to facilitate, but also obstruct, others goal achievement [2]. Cooperation and competition are two common and opposite models of interpersonal exchange [4]. A significant association between cognitive performance and inter-brain connectivity measures was founded [5]. Inter-brain synchrony increased when subjects were more cooperative with each other [32]. Earlier work investigated how cooperation and competition is influenced by creativity [5] [6], feedback [1] [7] [8] [33] [9] [10] [11] [12] [13] [14], personality [2] [33] [11] [14], emotion [15] [16] and belief [17] and strategies [13] [9] [10] [1] [18]. These factors are summarized in the following paragraphs. Literature overview of neural studies about cooperation and competition is shown in Appendix.A.5.

Personality An increased left The Prefrontal Cortex (PFC) responsiveness was found for subjects who has higher behavioral activation system rating (which means more self-motivated) in case of both cooperation and competition conditions [2]; subjects with higher behavioral activation system ratings showed greater frontal left activity during the cooperative task [2] and responded in greater measure to post-feedback condition with better real performance [1].

Feedback A worse performance after the negative feedback in the form of a specific pattern of brain activation involving the The Dorsolateral Prefrontal Cortx (DLPFC) and the superior frontal gyrus [9]. Post-feedback induced a decreased inter-brain synchrony [9].

Belief Inter-brain synchronization in P3b during cooperation suggested that a cooperative relationship is built up when the memory system (which support belief updating) of two interacting person reach a high level of coordination [17].

Both behavioral performance and physiological measures exhibited higher variance in holistic than in analytic subjects [34]; differences in amplitude and P300 latency suggest that decision making was easier for the holistic subjects in the cooperation condition, in contrast to analytic subjects for whom decision making based on these measures seemed to be easier in the competition condition [34].

Creativity Strong interpersonal brain synchronization between group members as evoked in two low-creative subjects, this interpersonal brain synchronization in right DLPFC and right Temporal-Parietal Junction (TPJ) covaried with the creative performance and cooperation [6].

Neural Networks Involved During Cooperation and Competition As for the neural networks involved during cooperative and competitive behaviors, involvement of relevant prefrontal areas has been founded [5] [8] [2] [9] [10] [11] [12] [14] [19]. Particularly, higher PFC activity was related with post-feedback than pre-feedback [8]; brain activation in DLPFC was related with negative feedback [13] [18] [1] [9] [7] and the creative performance [6]. However, although cooperation and competition share some important neural pattern, they do have some differences: INS increased in the right DLPFC and right Temporal-Parietal Junction (TPJ) only on cooperation [19]; brain activation in Inferior Frontal Gyrus (IFG) reduced/increased during cooperative/competitive interaction [20]; greater beta (12-24Hz) activation in the DLPFC when participants defect; there is a greater general amount of activated to defection as compared with cooperation [18];a stronger interpersonal brain synchrony was evoked between the regions in prefrontal and posterior temporal regions in the cooperation conditions, as compared with the competition mode [19].

2.2 Neural Systems Involved In Social Interaction

Social interaction contains two main neural systems, which are Mirror Neuron Systems (MNS) (includes the primary motor cortex and posterior parietal cortex) and Mentalizing System (MS) (consists of the TPJ,The Prefrontal Cortex (PFC)). These two systems are shown in Fig.2.1.

2.2.1 Mirror Neuron Systems

Mirror neurons, which respond similarity to both performing an action and observing the same action, was proposed to be involved in learning ability by imitation, to understand other peoples actions, to simulate other people's intentions, thoughts,

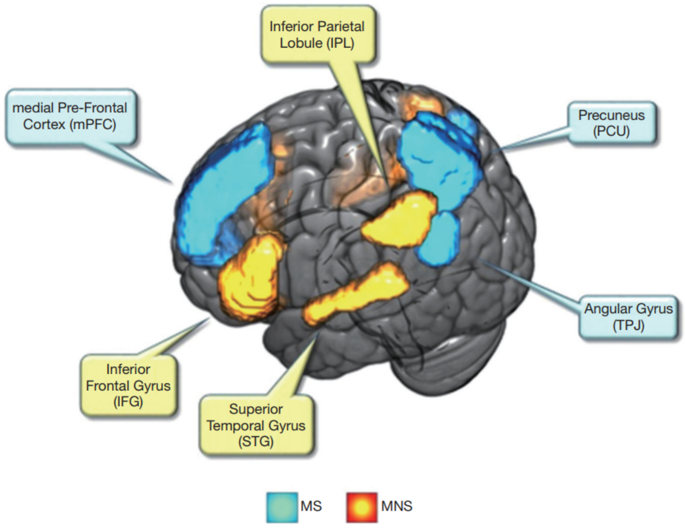


Figure 2.1: Brain regions considered for the MNS and the MS masks (both hemispheres).Adopted from Chiara Begliomini et al. [35].

and even emotions [36]. In human brains, the MNS (Fig.2.1) consists of the inferior frontal gyrus (which can provide additional supplemental information, such as the goal of the action) and inferior parietal lobe (which is related to language, motor and sensory detection) [37]. MNS was first discovered in monkey [38] and then be identified in human [39] [40]. Acting in a social context induced analogous modulations of motor and sensorimotor regions in observer and actor [40].

2.2.2 Mentalizing Systems

Mentalizing is responsible for understanding others intentions or emotions by their gestures, behaviors and facial expressions. The TPJ and PFC are two brain regions that are associated with mentalizing process. Activation in the TPJ manipulates memory, attention, language and social cognition [41]. PFC is responsible for the planning, regulation, integrating of information, and other high cognitive functions [37] and it is related to INS [42] [43] [10], such as INS existed in the Dorsomedial Prefrontal Cortex (dmPFC), during cooperative interaction. [42].

2.3 Functional Connectivity

NS were quantified by FC, which includes ISPC, spectral coherence, PLI, power correlation and MI.

2.3.1 Intersite Phase Clustering

ISPC means clustering in polar space of phase angle differences between electrodes, voxels, or neurons and it calculates the average of phase angle differences between electrodes over time and/or over trails.

$$ISPC_f = \left| n^{-1} \sum_{t=1}^{n} e^{i(\phi_{xt} - \phi_{yt})} \right| \tag{2.1}$$

If ISPC is computed over time, n is the number of time points, and ϕ_x and ϕ_y are phase angles from electrodes x and y at frequency f. If ISPC is calculated over trails, t refers to trail and n refers to the number of trails instead of the number of time points.

The averaged phase angle difference between two signals over time and/or frequency

2.3.2 Spectral Coherence

Spectral coherence is similar to ISPC, but the phase values are weighted by power values, so spectral coherence are likely to be influenced by strong increase or decrease in power. For example, if connectivity increases but power simultaneously decreases, spectral coherence may provide biased results.

$$Coher_{xy} = \left| \frac{S_{xy}}{S_{xx} S_{yy}} \right| \tag{2.2}$$

S_{xy} is the cross-spectral density between activities at electrode X and Y, and S_{xx} and S_{yy} are the auto-spectral densities for electrodes X and Y. Eq.2.3 equals Eq.2.2 in a Euler-like format.

$$Coher_{xy} = \frac{\left| n^{-1} \sum_{t=1}^{n} |m_{tx}||m_{ty}| e^{i\phi_{txy}} \right|^2}{\left(n^{-1} \sum_{t=1}^{n} |m_{tx}|^2\right) \left(n^{-1} \sum_{t=1}^{n} |m_{ty}|^2\right)} \tag{2.3}$$

m_x and m_y are the analytic signals X and Y,ϕ_{xy} is the phase angle difference between electrodes X and Y, and t refers to trials and/or time points, depending on whether coherence is computer over time and/or over trials. The denominator is simply the product of the average power values from electrodes X and Y.

2.3.3 Phase Locked Index

Because effects of volume conduction are instantaneous within measurement capabilities of M/EEG acquisition within frequencies typically investigated in M/EEG research, spurious connectivity results that are caused by two electrodes measuring activity from the same source will have phase lags of zero or π (π if the electrodes are on opposite sides of the dipole).

The phase lag index measures the extent to which a distribution of phase angle differences is distributed toward positive or negative sides of the imaginary axis on the complex plane (that is, whether the vectors are consistently pointing ”up” or ”down” in polar space when the imaginary axis corresponds to a vertical line). Thus, with the phase-lag index, the vectors are not averaged, but instead, the sign of the imaginary part of the cross-spectral density is averaged.

$$PLI_{xy} = \left| n^{-1} \sum_{n}^{t=1} sgn(imag(S_{xyt})) \right| \tag{2.4}$$

in which $imag(s)$ indicates the imaginary part of the cross-spectral density at time point (or trial) t; sgn indicates the sign (-1 for negative values, +1 for positive values, and 0 for zero values).

2.3.4 Power Correlation

Phase-based connectivity analyses assume that the connectivity is instantaneous (although not necessarily with zero phase-lag), and at the same frequency. Power-based connectivity analyses do not have this constraint. Another feature of this method is that this measure ignores the temporal structure in the data, and treats the time series as realizations of random variables [44].

The Spearman coefficient measures correlation and is defined as the covariance of two variables, scaled by the variance of each variable.

$$r = \frac{\sum_{t=1}^{n}(x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^{n}(x_t - \bar{x})^2 \sum_{t=1}^{n}(y_t - \bar{y})^2}} \tag{2.5}$$

The numerator is simply the sum of variables x times variable y at each time point (or trial) t, after subtracting the mean of each variable (the bar on top of the variable indicates the mean). The denominator is the variance of each electrode.

Spearman coefficient is applied in this paper rather than Pearson coefficient as the power of brain signals does not normalized distributed, which against the assumption of Pearson correlation [45]. Surprisingly, most studies applied Pearson correlation without any normality test [46]

2.3.5 Mutual Information

Entropy Entropy is the basic building block of mutual information and it measures uncertainty. To compute entropy with continuous data such as an EEG, first the data should be binned to create a histogram to calculate probabilities.

$$H(X) = -\sum_{i=1}^{n} p(x_i)log_2p(x_i) \tag{2.6}$$

where H is the measure of entropy, p is the probability of observing the i^{th} value of the bin series data x, and n is the number of bins. Entropy is not subject to power-law scaling effects over frequency and is also unrelated to the temporal structure of the data.

The number of bins into which to discretize the data influences the data distribution, and thus influence the entropy.

Joint Entropy Joint entropy is the total entropy of a pair of variables.

$$H(X,Y) = -\sum_{j=1}^{m}\sum_{i=1}^{n} p(x_i,y_i)log_2p(x_i,y_i) \tag{2.7}$$

Mutual Information Mutual information is the amount of the shared information between two variables.

$$MI(X,Y) = H(X) + H(Y) - H(X,Y) \tag{2.8}$$

MI can capture non-linear relationship, while other synchrony measurements (e.g. power correlation) can not. Another feature of this method is that this measure ignores the temporal structure in the data, and treats the time series as realizations of random variables [44].

2.3.6 Comparison of All Functional Connectivity Methods

Strength and weakness of all FC methods are listed in Tab.2.1.

<table>
<tr><th></th><th colspan="2">Features</th></tr>
<tr><td>ISPC</td><td>ISPC measures the clustering in polar space of phase angle differences between electrodes, voxels, or neurons</td><td rowspan="3">1. Phase-based connectivity analyses assume that the connectivity is instantaneous and at the same frequency [47]
2. Phase synchrony are computed from the frequency domain representation of a pair of signals, which represents across a set of observations (epochs or time windows) [44].</td></tr>
<tr><td>spectral-coherence</td><td>Spectral coherence is similar to ISPC, but the phase values are weighted by power values</td></tr>
<tr><td>PLI</td><td>1. Robust to the volume conduction (zero phase difference between two signals)
2. It assumes that both the phase lag and the frequencies of activities of the two electrodes are stationary for the duration of time used in the analysis</td></tr>
<tr><td>Power-correlation</td><td>This measurement ignores the temporal structure in the data, and treats the time series as realizations of random variables [44]</td><td></td></tr>
<tr><td>MI</td><td>1. MI is robust for quantifying the amount of information that is shared between two variables
2. It can identify patterns of connectivity regardless of the distribution of the data (e.g, linear, non-linear, circular)
3. MI ignores the temporal structure in the data, and treats the time series as realizations of random variable [44]</td><td></td></tr>
</table>

Table 2.1: Brief summarization of features of FC methods

2.4 Brain Network

FC of the brain is usually obtained by measuring a specific type of physical signal (e.g., blood oxygen level dependent contrast as in Functional Magnetic Resonance Imaging (fMRI) or magnetic field as in Magnetoencephalography (MEG)) from different regions and then comparing pairwise signals by means of some similarity measure (e.g., cross-correlation [48], transfer of entropy, spectral coherence [49], etc.) [50].

Graph theory is a mathematical framework for characterizing networks that can be represented as graphs containing nodes and vertices (for EEG connectivity, nodes and vertices are, respectively, electrodes and connectivity(strengths).

The advantage of graph theory analysis is that it offers useful and easy-to-interpret characterizations of multivariate network. Topological properties of networks are useful, such as community in brain network can help detect schizophrenia, Alzheimer's disease and other cognitive disorders since neuropsychiatric disorders can be thought of as dysconnectivity syndromes [51]; Katelyn L. Arnemann et al. [52] used modularity of brain network to detect patients with brain injury.

2.4.1 Network Formation

Standard networks can be represented by adjacency matrices, indicating the presence and the intensity of connections among the brain's units [50].

Nodes and edges represent interested electrodes and FC respectively. In weighted network, edge are weighted by FC strength. In order to find significant edges among the team brain network, threshold (one standard deviation above median of intra- and inter-brain NS) is applied into the weighted team brain network. Another threshold applied in this study is that: for intra-brain network, threshold is visually detected by intra-brain neural synchrony distribution (since there is always a clear gap in distribution that separate weak intra-brain ns clusters and high intra-brain NS); for inter-brain network, top 10 highest INSs were chosen since there is no gap in distribution and INSs are strongly clustered.

$$e_{ij} = \begin{cases} r_{ij}, & if r_{ij} \geq T \\ 0, & otherwise \end{cases}$$

where r_{ij} is the weight and T is the threshold.

With regard to the threshold, some papers specify the number of connections and then keep the k strongest connections, setting the rest to zero [47]. This approach is not optimal for condition comparisons because the relative strengths of connectivity may differ across conditions. The threshold of one standard deviation above the median connectivity value is recommended by Mike X Cohen [47] as he stated that this threshold seems to work well in the EEG datasets in his studies. Nonetheless, the threshold can be any reasonable value, such as .5 [53].

Notably, this threshold was only applied to find strong NS and it was not employed for calculating topological properties.

2.4.2 Network Topological Properties

Topological properties are useful in detecting some illnesses. For example, Liang Wang et al. [23] found that brains with attentiondeficit/hyperactivity disorder exhibit large local efficiency and smaller global efficiency as compared with healthy brain. Brain hubs, which are measured by centrality, are central in brain communication and neural integration [22].

Small-world networks, which is quantified by small-world-ness, are formally defined as networks that are significantly more clustered than random networks [54]. Health brain is small-world network because health brain has evolved both to maximize the efficiency of information transfer and to minimize connection cost, at all scales of space and time [51]. Small-world-ness is influenced by cognitive-related-illness(s.t., schizophrenia [55]).

Three topological properties were calculated in this paper: Global Efficiency, Small-World-Ness and betweenness centrality.

Global efficiency

Efficiency measures how efficient a network exchanges information. In neuroscience, global efficiency has been linked with a range of cognitive variables, including spatial orientation [56], memory retrieval [57], mathematical abilities [58], intelligence [59] and creativity [60].

The average efficiency of a network G is defined as:

$$E(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d(i,j)} \tag{2.9}$$

where n denotes the total nodes in a network and $d(i,j)$ denotes the length of the shortest path between a node i and another node j. The global efficiency of network G is defined as:

$$E_{glob}(G) = \frac{E(G)}{E(G^{ideal})} \tag{2.10}$$

where G^{ideal} is the graph, where all possible edges are present.

Small-World-Ness

Path length

Path length measures how efficient the information transports on a network. The path length measures the average minimal distance between the 2 nodes, defined as:

$$L = \frac{1}{N(N-1)} \sum_{i \neq j, i, j \in G} d(i,j) \tag{2.11}$$

where $d(i,j)$ is the shortest distance between node i and j.

Clustering Coefficient A clustering coefficient is a measure of the degree to which nodes in a graph tend to cluster together. Clustering coefficient is based on transitivity is explain in Eq.2.12

$$c = \frac{3 \times number\,of\,triangles}{numberofpathoflength2} \tag{2.12}$$

where a 'triangle' is a set of three nodes in which each contact the other two.

Small-World-Ness The network G is said to be a small-world network if Small-World-Ness (SWN) is greater than 1. SWN is defined in Eq.2.13.

$$S = \frac{\frac{C}{C_{rand}}}{\frac{L}{L_{rand}}} \tag{2.13}$$

where L is the mean value of the minimum path length over all node pairs of network G and C is clustering coefficient. L_{rand} and C_{rand} are the corresponding quantities for the corresponding $E-R$ random graph, which has the same amount of nodes and edges of network G.

Definition of SWN does not remain the same in papers. Beside global clustering coefficient (Formula.2.12, clustering coefficient can also be explained locally [61], which will lead SWN value a slightly different. Furthermore, there are other ways to quantify SWN [62] [63]. This research only calculated SWN based on one definition based on the time constraint.

Betweenness Centrality

Indicators of centrality identify the most important vertices within a graph and betweenness centrality is a centrality measurement based on shortest paths. The betweenness centrality of a node v is defined as:

$$g(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{2.14}$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through v. For weighted network, the shortest path between nodes is calculated by the sum of weights of edges rather than the number of edges.

There are many ways to quantify centrality in graph theory, such as degree centrality, closeness centrality and eigenvector centrality, just name a few. Since centrality measures how ”important” a node is in the network, the world ”importance” has a wide number of meanings, leading to many different definitions of centrality. Betweenness centrality captures network characterization by walk structure, as it is the number of shortest paths which pass through the given vertex. Different centrality measurements have different features, which may draw different brain hubs. This diversity makes result comparison among papers difficult.

Chapter 3

Method

To explore team neurodynamics during cooperation and competition with EEG, the pong-game is designed to imitate cooperative and competitive social interaction since EEG is very sensitive to noise while this game only requires finger movements to minimize noise. To obtain clean brain signals, EEG signals were preprocessed to remove noise. Team neurodynamics are quantified by NS, which are calculated by FC methods. Following calculating FC, graph theory was applied to visually explore functional brain structure. Strong neural synchrony during cooperation and competition were detected by applying threshold to intra- and inter-brain synchronies. To find different neural patterns between cooperation and competition, statistical significant INS was calculated.

This section introduces the workflow, experiments, the participants population, neural synchronization analysis, FC robust analysis and how to calculate statistically significant INS between cooperation and competition.

3.1 Participants

The experiments were conducted in the DBS lab at the university of Twente. Written informed consent was obtained from each subject after the explanation of the study, which was approved by the ethics committee of Electrical Engineering, Mathematics and Computer Science faculty of the university of Twente,the Netherlands. The participants consisted of healthy subjects (N=18), with a mix of gender (6 female and 12 male) as well as age $(M = 30.94, SD = 10.62)$. The participants were contacted via emails and given further instruction once they accept the request to participants in the research. They reported no history of neurological or chronic pain disorders, or other significant health issues. They were instructed to avoid the use of alcohol and narcotics, and the over-consumption of coffee for at least 24 hours before the experiment; sufficient sleep was recommended before the experiment.

Each participant was given complete details of the experimental procedure and was familiarized to cooperative/competitive pong-games at the onset of the experiment. Written consent forms were obtained from all participants.

3.2 Cooperative/Competitive Interaction

To simulate competition and cooperation between dyads, pong-game (similar to that of a table tennis) was designed, in which dyads were required to bounce the ball back with the paddles. This game was designed based on EEG constraint: minimizing body movements to reduce the signal noise. Therefore, this experiment only requires subject to use two fingers to control the game.

In competition scenario, two subjects controlled one paddle respectively to move up and down to hit the ball back. Once the subject missed a ball, the other subject would win one score. The subject who first gained 10 scores would win this game. Illustration of this competitive game is shown in Fig.3.1b.

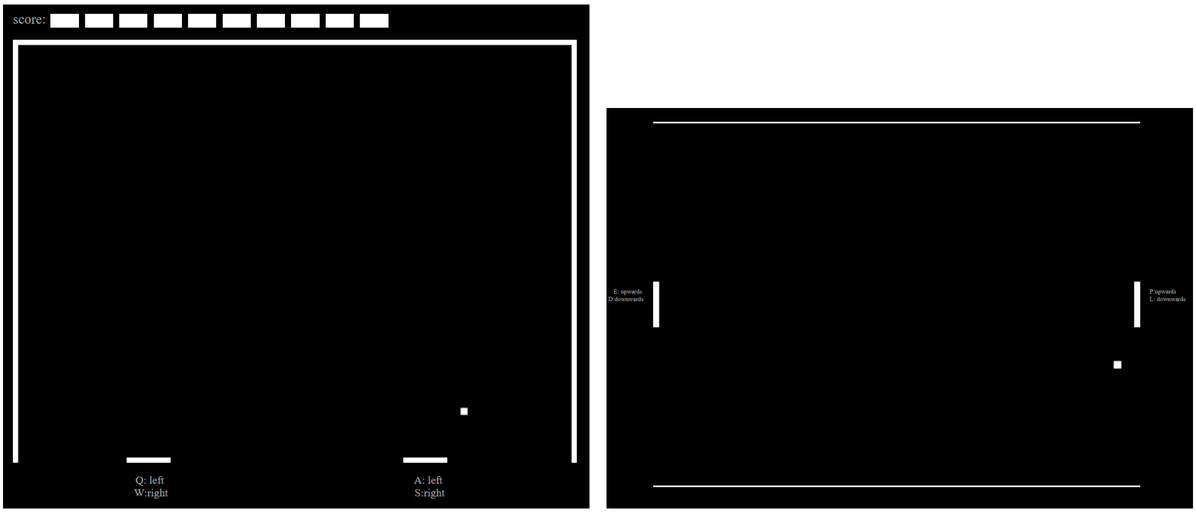
As for cooperative game (Fig.3.1a), two subjects were told to work as a team. They had 10 scores at first, which was shown on the top of the court. Each paddle can only move half width of the court (e.g, the left paddle can only move over the left-half-side of the court and cannot move to the right-half-side). If the team missed a ball, they would lose one score; if they lose all 10 scores, they would lose the game. Different with competitive game, the cooperative experiment requires subjects to discuss strategies about how to improve team-performance before game started.

For each dyad, there are 4 trails for cooperation and competition respectively. In order to add the difficulty to the game, the ball would speed up if subjects kept succeeding in hitting the ball back.

3.3 Experiment Procedure

Experiments were conducted in a lab, which contains all required equipment. Two subjects were seated in arm-chairs alongside with each other, playing competitive/cooperative pong-game together with Twente Medical Systems Internation B. V (TMSI) EEG equipment.

The experiment consisted of two blocks: cooperative-game-playing and competitive-game-playing. Each block contains 4 trials. During cooperative session, two subjects were required to discuss strategies to improve game-performance. Each session was separated by a period of 10s to relax subjects. The entire experiment took about 1 hours.



(a) Illustration of computer-based cooperative Pong-game. The team has 10 scores at first, which are shown on the top in ten solid rectangles, each subject controls one paddle to move left and right with two keys. Once the team loses a ball, they lose one score. Team performance is measured by game duration

(b) Competitive Pong-game. Each subject controls one paddle to move up and down with two keys. If one subject misses the ball, another subject will win one score. The winner is the subject who first wins 10 scores

Figure 3.1: Screen-shots of cooperative/competitive computer pong-game

A complete step-by-step description of the experimental protocol can be found in Appendix.A.4.

3.4 Analysis Work-flow

Fig.3.2 illustrates analysis workflow, which includes three phrases: EEG signal pre-possessing, NS calculation and brain network formation.

There are 6 steps during the preprocessing phrase. First, raw data was extracted based on game-start and game-end event trigger.Then, a band-pass filter (1-45Hz) was applied to extract interested frequency band and remove 50Hz line noise. In order to minimize computer computation workload, signal was down-sampled from 1284Hz into 512Hz. The first and last 5 second data were removed since there were delays in these moments. DC signals were removed. To increase data quality, noise was removed by multiple artifact rejection algorithm (MARA). Following data cleaning, epochs were extracted based on 1-second window with .5 second overlapping. Rather than averaging 1 second of the data, this pipeline was also conducted based on the whole last 30 and 15 seconds of the data, the results can be founded in Appendix.A.3 and Appendix.A.2 respectively. To increase the data quality, dataset which contained more than 60% noise components in ICA analysis were removed.

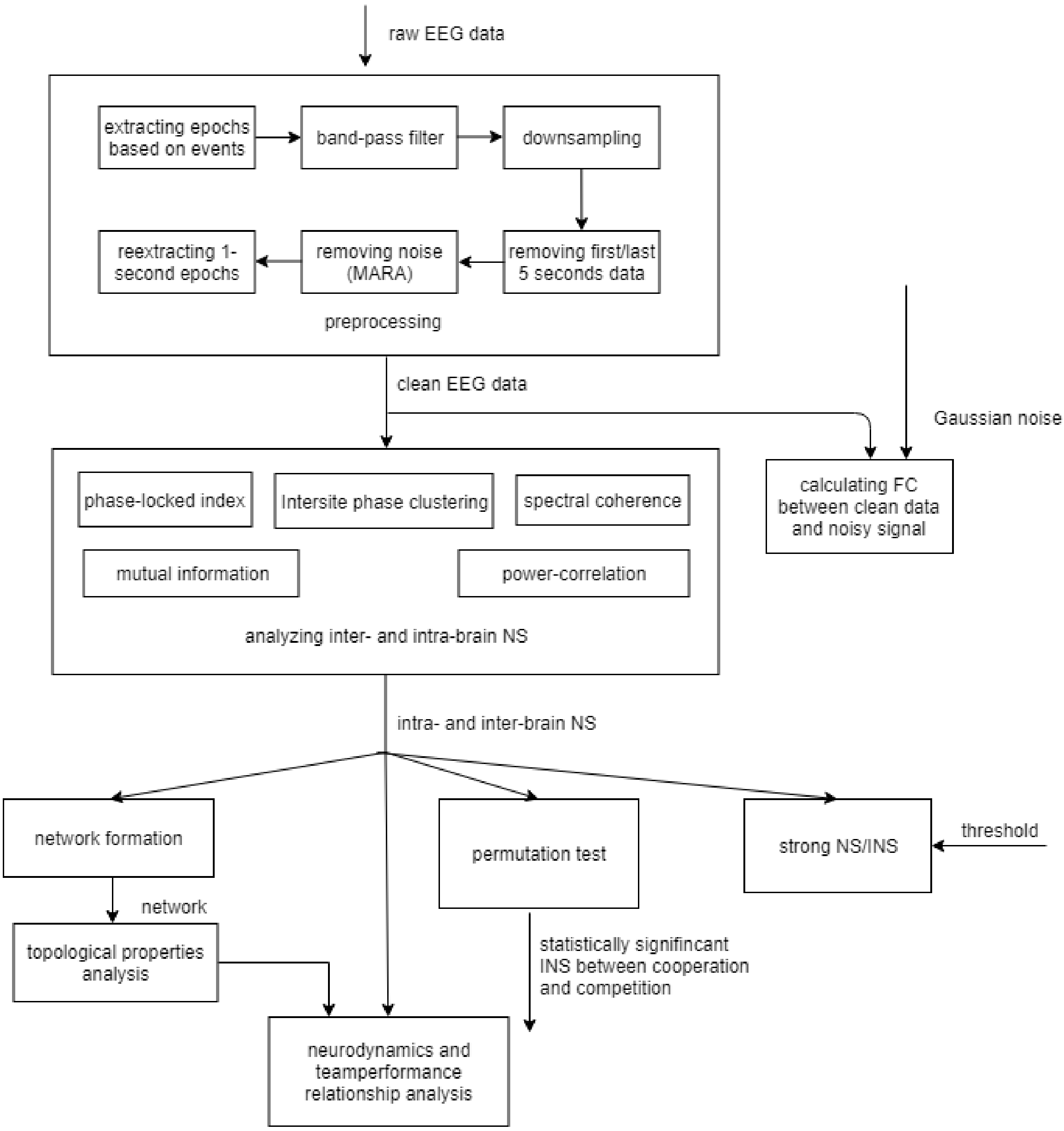


Figure 3.2: The workflow of this study. It contains three phrases: prepossessing, NS calculation and network formation.

Accordingly, 25 competitive trials and 17 cooperative trials are obtained from 32 trials (8 dyads x 4 competitive/cooperative trials for each dyad).

Following data-cleaning, NS were calculated on different FC methods. Based on previous studies [64] [40], brain signals were filtered by beta frequency band since beta brain wave dominates human normal waking state of consciousness when attention is directed towards cognitive tasks and the outside world. Differently, for MI-based FC method, gamma band was applied based on previous studies [31] . Notably, to compare intra- and inter-brain strength, NS are normalized into 0 to 1 on team level for each FC method (the largest intra- and inter-brain Fc value is normalized into 1 and the smallest value is normalized into 0).

Following NS calculation, NS were applied into 4 different analyses: (1) topological properties analysis; (2) statistically significant INS analysis; (3) strong NS/INS analysis; and (4) behavioral data analysis.

Regarding topological properties analysis, weighted intra- and team-brain networks were generated first. Then, three topological properties-GE, SWN and betweenness centrality-were calculated based on brain networks.

Concerning statistically significant INS between cooperation and competition, the permutation test with 500 shuffles was applied. To further explore whether these results are valid, one significant INS were illustrated over time and frequency.

With regards strong NS/INS analysis, two different types of thresholds were applied into intra- and inter-brain NS :(1) one standard deviation plus median of intra- and inter-brain NS without outliers, which are more than three scaled median absolute deviations; (2) for intra-brain NS, the threshold was visually detected based on intra-brain neural synchrony distribution; for inter-brain NS, top 10 highest INS were chosen. The reason why chosen these thresholds were discussed in Sec.2.4.1.

As for behavioral data analysis, in order to find the relationship between team-performance and INS/GE, game-performance was quantified by game-duration and one degree polynomial curves were applied between these two predictors (game duration and INS/GE).

Robust of FC methods was analyzed with the clean EEG signals. First, FC of two identical clean brain signals was calculated and the result should be 1 for all normalized NS measurements. Different level of white noise was added into the clean brain signal to obtain noise-contaminated brain signal with different Signal to Noise Ratio (SNR). FCs were calculated between the clean signal and noisy data to test how Gaussian noise influences NS.

3.5 Neural Synchrony Analysis

Phase-based and power-based neural synchrony measurements are based on time-frequency analysis. This study applied a sinusoidal wavelet (short time discrete Fourier transform) to transform brain signal from time-amplitude into time-frequency domain. In this transform, the number of cycles were increased slowly with frequency: overlapping time window began with a 3-cycle wavelet (with a Hanning-tapered window applied) and the number of cycles in the wavelets used for higher frequencies continued to expand slowly, reaching half (0.5) the number of cycles at its highest frequency. This feature offers better frequency resolution at higher frequencies than a conventional wavelet approach that uses constant cycle length [65]. Time scale is 0.

As for MI-based FC method (a non-frequency-decomposition-required method), 1000 bins were applied to create signal distributions.

Based on previous paper [31], signals were filtered by gamma band (31 to 45Hz) before MI calculation. For other FC methods, beta brain waves(13 to 30Hz) was employed as the beta rhythm is associated with normal waking consciousness.

FC was calculated between each electrode pairs ($21 \times 21 = 441$,21 electrodes from player A and 21 electrodes from player B), averaged over time, frequencies, epochs and trials for different conditions. For example, each condition has ISPC matrix in $time \times frequency \times epoch \times trials \times 441$ format. There are 25 trials on competition and 17 trials on cooperation. The ISPC-based team NS matrix is to average $time \times frequency \times epoch \times trials \times 441$ over the first 4 dimensions to get 1×441 matrix, where each column represents one electrode pair.

Instead of 1-second-epoch-ed data, FCs were also calculated based on the last 15 and 30 seconds, the corresponding results are shown in Appendix.A.2 and Appendix.A.3.

FC was also calculated over frequency or time to inspect weather NS is stable.

3.6 Functional Connectivity Robust Analysis

Two clean signals were randomly chosen (one from subject 1's Fp1 electrode on cooperation while the other clean signal was from subject 2's Fp1 electrode during competition).

For each clean data,different levels of Gaussian noise was added into the clean signal to create noise-contaminated brain signals with different SNR. In this paper, 5 noisy signals with 2db, 4db, 8db and 10db signal-to-noise ratio were generated based on the clean data. The lowest SNR is 2db because results show that all FC methods already lose power at this noise level. To test FC robust, NS was measured between the clean data and the noise-contaminated data.

The clean signal is denoted as u and the Gaussian noise is denoted as n with zero man and σ_n^2 variance. It is assumed that Gaussian noise is not correlated with the signal u. The noise-contaminated data is

$$v = u + n$$

Accordingly, the SNR is

$$SNR[db] = 10 \times log_{10}(\sigma_u^2/\sigma_n^2)$$

where σ_n^2 and σ_u^2 are the variance of Gaussian noise and the clean signal respectively.

3.7 Linear polynomial curves

To fit a line between game-duration (predictors) and INS or GE value (response variables), one degree polynomial curves are applied.

$$Y = p_1 * x + p_2 \tag{3.1}$$

Y is response variables, x is the predictor value.

3.8 Statistically significant Inter-Brain Synchrony

In order to find statistically significant INS between cooperation and competition, a permutation test with 500 shuffles was applied. The null hypothesis is for each INS pair, the mean of INS during cooperation and competition are the same. However, t-test was applied in most papers without any normality test [66] [42] [67] [4]. Some papers also applied some non-parametric tests, such as the wilcoxon rank-sum test [68] [46], which equals to replacing each observation by its rank, then do a permutation test using the sum of the (ranks of the) responses.

Suppose I_{coop} and I_{comp} represents the inter-brain synchrony between all pairs of subjects during cooperation and competition respectively. Note that each of these matrices have 3 dimensions $(i \times j \times n)$ where $(i = 1, 2, \ldots 21)$ and $(j = 1, 2, \ldots 21)$ represent the EEG channels of player A and player B respectively and n represents the number of trails (or pair of subjects) in our experiments. Competition consists of 23 trials and cooperation contains 17 trials.

In order to find statistically significant INS between different experimental scenarios, the permutation test was applied. First, for each INS pair, INS were averaged over trials for cooperation and competition. For example, to determine if the edge linking the prefrontal area under the electrode labelled Fp1 in subject A with the corresponding prefrontal location in subject B, was significantly different in two scenarios, two vectors $\{I_{comp}(1,1,n)|n = 1,2,\cdots 23\}$ and $\{I_{coop}(1,1,n)|n = 1,2,\cdots 17\}$ were averaged over trials to obtain $\overline{I_{comp}(1,1)}$ and $\overline{I_{coop}(1,1)}$. Then, these two averaged INS based on each condition was subtracted with each other to calculate observed value of the test statistic, which denotes T_{obs} in this paper. For example, $T_{obs} = \overline{I_{comp}(1,1)} - \overline{I_{coop}(1,1)}$. Next, trials on cooperation and competition were shuffled with each other 500 times. On each time, aforementioned steps were repeated to calculate INS difference in two different condition. After obtaining 500 calculated differences, the one-sided p-value of the test is calculated as the proportion of sampled permutations where the difference in means were greater than or equal to T_{obs}. For statistical comparison, a strict threshold on p-values at 0.01 was applied. To correct the type 1 errors, multiple comparisons were compensated by applying false discovery rate correction at a significance level of 0.5%.

False discovery rate

The false discovery rate (FDR) is a method of conceptualizing the rate of type I errors in null hypothesis testing when conducting multiple comparisons.

Based on definitions,

$$Q = V/R = V/(V+S) \tag{3.2}$$

where V is the number of false positive (Type I error), S is the number of true positives (a.k.a "true discoveries"), R (R=V+S) is the number of rejected null hypotheses (a.k.a "discoveries", either true or false),Q is the proportion of false discoveries among the discoveries (rejection of the null hypothesis). The false discovery rate (FDR) is defined as:

$$FDR = Q_e = E[Q] \tag{3.3}$$

where Q is defined to be 0 when R = 0. One wants to keep FDR below a threshold q. To include the case when R =0 , formally

$$FDR = E[V/R|R > 0] \dots P(R > 0) \tag{3.4}$$

Chapter 4

Results

Bain map of electrode distribution and the corresponding brain area for each electrode can be found in Appendix.A.7.

4.1 Robust of Neural Synchrony Measurements

The first research task is to analyze to what extent FC methods are robust to noise. NS measurements include power-correlation, ISPC, PLI, spectral-coherence and MI.

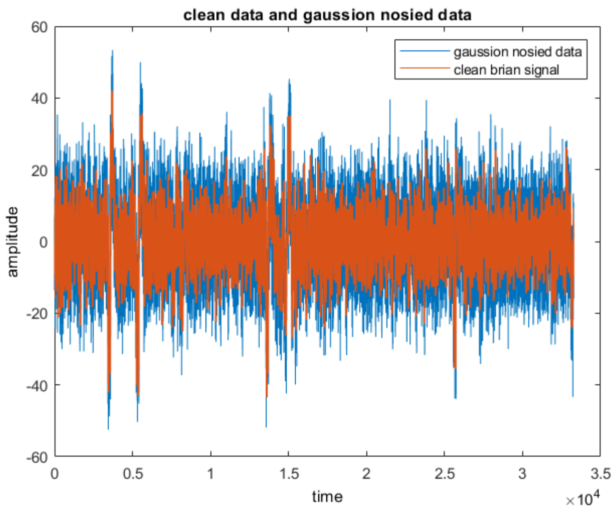
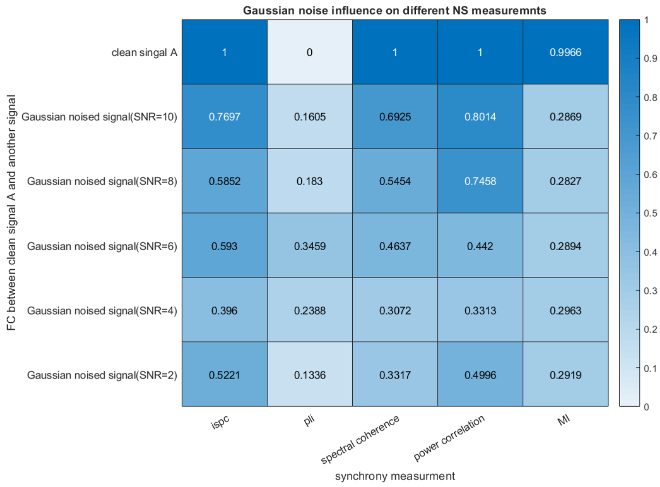
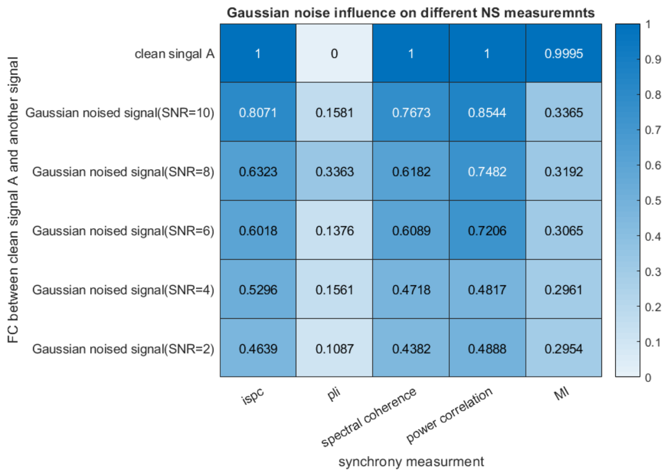


Figure 4.1: Time-amplitude plot of the clean data and the noisy data with 2db SNR. The red line represents the clean data while the blue line represents the noisy data with 2db SNR.

The clean brain signal extracted from Pz electrode from one subject during competition, is shown in Fig.4.1 with read color, noisy data with 2db SNR is shown in blue color.



(a) Clean data from person 1



(b) clean data from person 2

Figure 4.2: Heat-map of FC between clean and noisy brain signals. Row represents how the clean signal synchronized with the noisy brain signals with different SNR. For example, the first row represents how to identical clean signals synchronized with each other, the second row represents how the clean signal synchronized with the noisy signal with 10db SNR. Columns represent different FC methods, from the left to the right, 5 columns respectively represent ISPC, PLI, spectral coherence, power correlation and MI. The first row should be 1 for all normalized FC since two identical clean signals should be theoretically perfectly synchronized with each other. PLI is zero for the synchronization between two identical signals. The plots shows ISPC, spectral coherence and power correlation shows that FC decreases as SNR decreases. FC cannot quantify NS if data is heavily contaminated by noise. MI is very sensitive to noise since MI drops dramatically if noise is added into the clean signals. PLI is not influenced by noise.

Fig.4.2 shows how noise influences NS. The clean signals in Fig.4.2a and Fig.4.2b are from one subject' Fp1 electrode during cooperation and another subject' Fp1 electrode on competition respectively.

After contaminating the clean signals with white noise, 5 noisy signals with 10db, 8db, 6db, 4db, 2db SNR were generated. Each row (except the first row) represents how the clean signal synchronized with noisy data. For example, the second row of Fig.4.2a and Fig.4.2b shows synchronization between the clean signal and the noisy data with 10db SNR.

The summarization of robustness of all FC methods are listed in Tab.4.1. Since MI- and PLI-based FC methods are less robust, the following analysis results based on these two methods are only listed in Appendix.A.1.

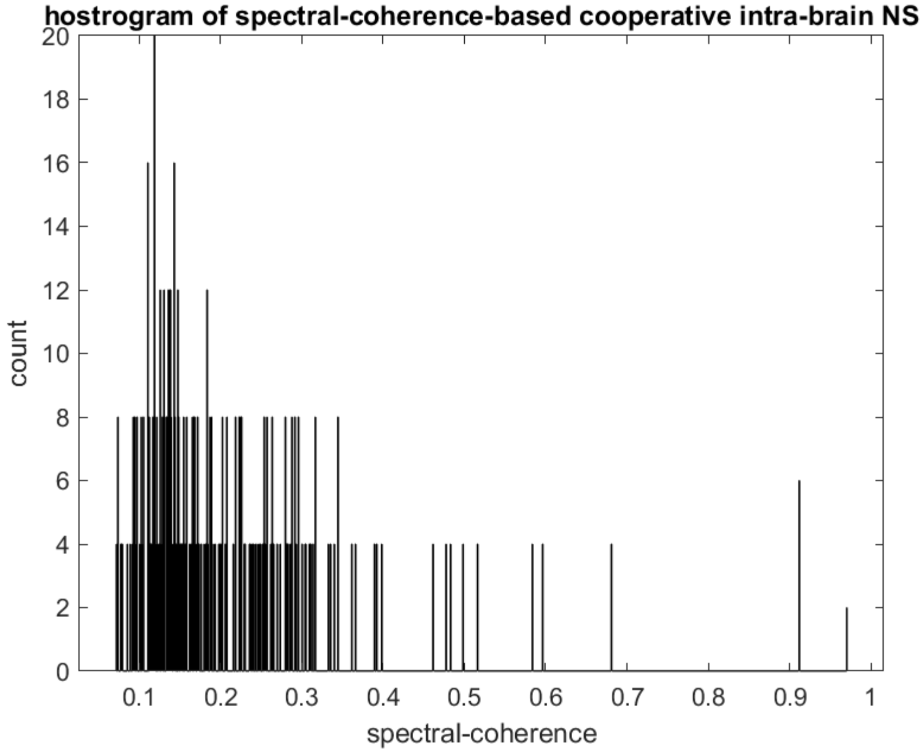
FC methods	Robustness
MI	MI is most sensitive to noise
ISPC	ISPC decreases as noise increases
PLI	1. PLI can not captures some significant NS 2. Noise does not influence PLI
Spectral coherence	The similar pattern with ISPC
Power correlation	Power-correlation is least sensitive to noise

Table 4.1: Summarization of robustness of five FC methods

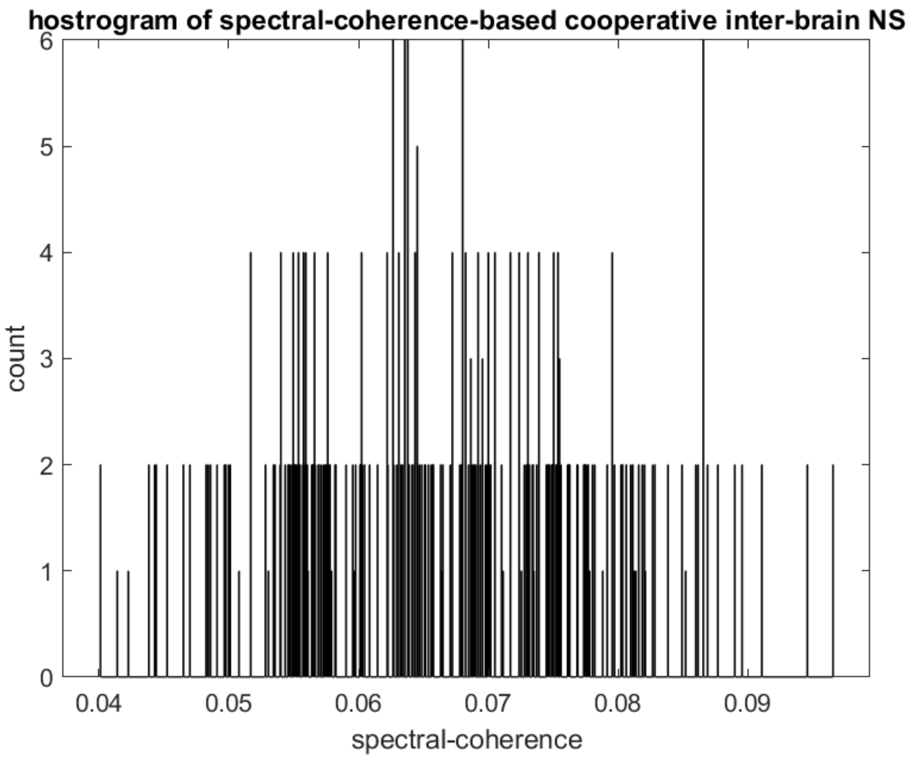
4.2 Strong Neural Synchrony

The second research task is measuring NS during cooperation and competition. NS are shown in the team brain network format with intra- and inter-brain NS. Based on the previous findings(Fig.4.2), results from less-robust FC methods-MI-based and PLI-based NS- are listed in Appendix.A.1.2.

In adjacency matrix, $FP1$,FPz,$FP2$,$F7$,$F3$,Fz,$F4$,$F8$,$T7$,$C3$,Cz,$C4$,$T8$, $P7$,$P3$,Pz,$P8$,$O1$,Oz,$O2$ are EEG electrodes from subject 1. $FP1_2$, FPz_2, $FP2_2$, $F7_2$, $F3_2$, Fz_2, $F4_2$, $F8_2$, $T7_2$, $C3_2$,Cz_2,$C4_2$,$T8_2$,$P7_2$,$P3_2$,Pz_2,$P8_2$,$O1_2$,Oz_2,$O2_2$ are EEG electrodes from subject 2. The color-bar on the right shows FC strength. The arbitrary threshold: one standard deviation above median is applied to generate these adjacency matrix: Fig.4.4, Fig.4.6,Fig.4.8 respectively show ISPC-, power-correlation- and spectral-coherence-based adjacency matrix.

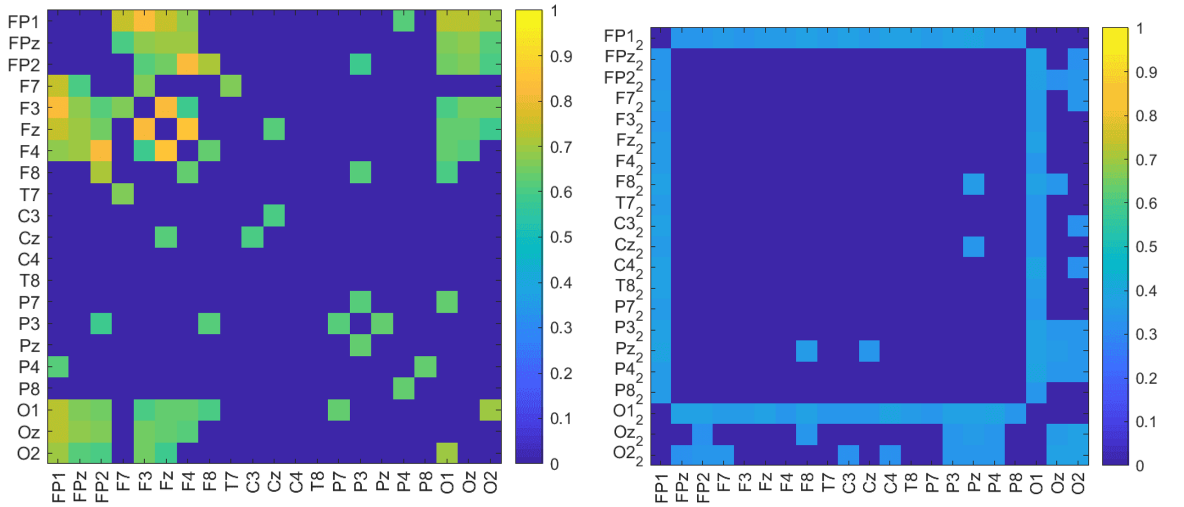


(a) Distribution of spectral-coherence-based competitive intra-brain NS. X-axis shows the spectral-coherence value while y-axis shows the count. There is a gap around 0.45 spectral-coherence-value: on the left of this threshold, NS are highly clustered; on the right, there are few strong NS.



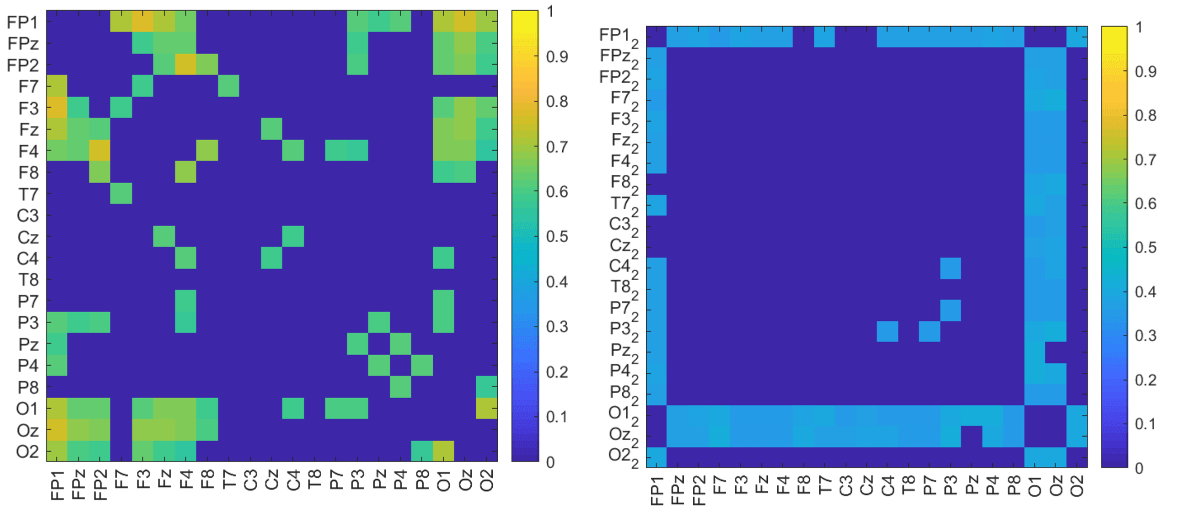
(b) Distribution of spectral-coherence-based competitive INS. Different with Fig.4.3a, there is no gap clearly that separate the weak and strong NS, instead in this plot INS clustered with each other. Therefore, top N (for example, 10) highest INS are chosen to be the strong NS

Figure 4.3: Distribution of spectral-coherence-based NS on competition



(a) Adjacency matrix of ISPC-based intra-brain network during competitive interaction

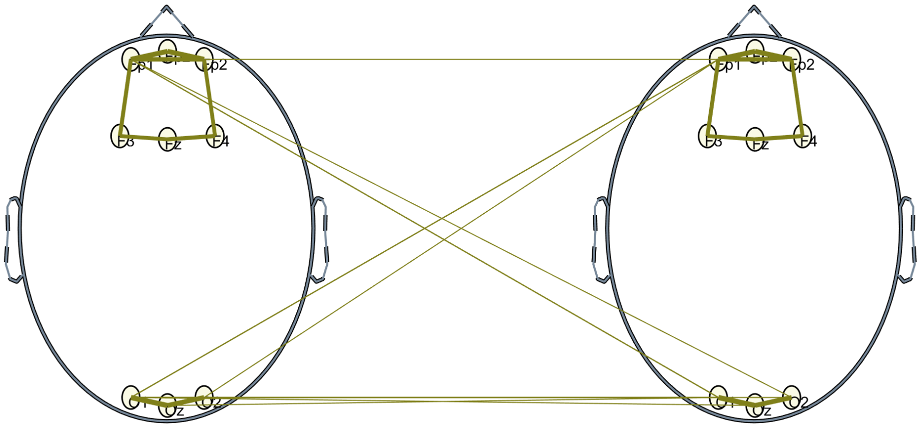
(b) Adjacency matrix of ISPC-based inter-brain network during competitive interaction



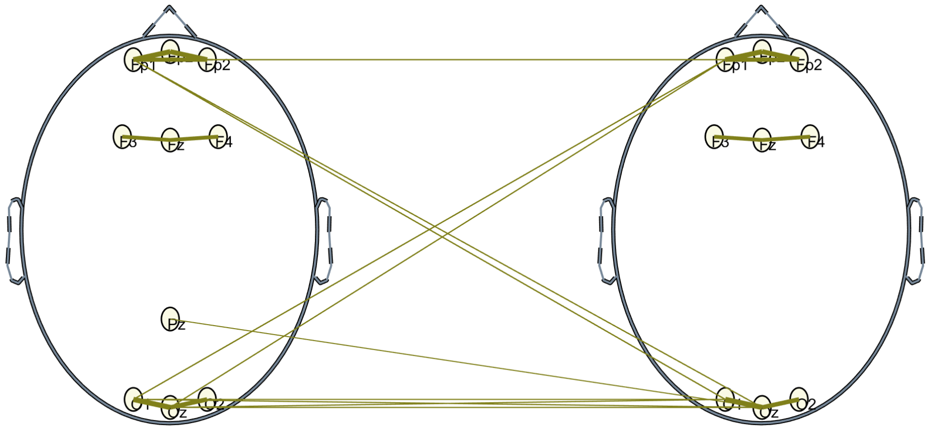
(c) Adjacency matrix of ISPC-based intra-brain network during cooperative interaction

(d) Adjacency matrix of ISPC-based inter-brain network during cooperative interaction

Figure 4.4: Adjacency matrix of ISPC-based team brain network during cooperative/competitive interaction. Intra-brain NS are more strong than INS. There are similar amount of intra-/inter-brain NS during cooperation and competition. Intra-brain NS, which are shown in (a) and (c), indicate brain activities at pre-frontal lobe are highly synchronized with occipital lobes; brain signals at the frontal lobe are highly synchronized with occipital,frontal and prefrontal lobes respectively; INS, which is shown in (b) and (c),indicates signals at occipital and prefrontal lobes are strongly synchronized with the other whole brain.

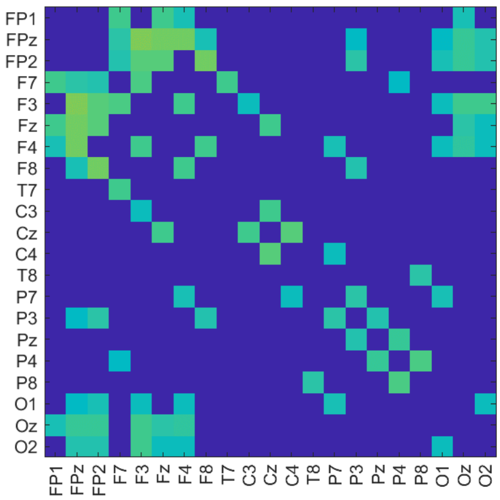


(a) ISPC-based team brain map during competitive interaction

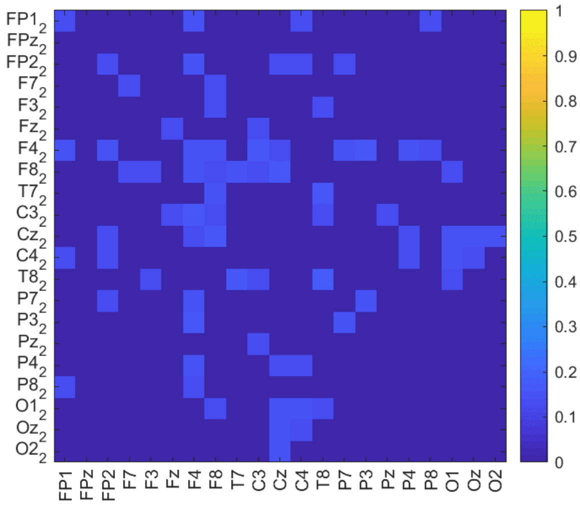


(b) ISPC-based team brain map during co-operational interaction

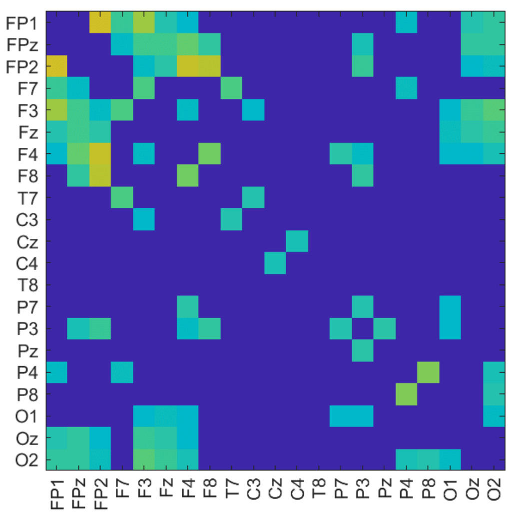
Figure 4.5: Team brain maps of ISPC-based team brain network. Line thickness indicates neural synchrony strength. Within-brain lines represent intra-brain synchronizations while inter-brain lines represent inter-brain synchronization. Intra-brain NS with lower power-correlation value (smaller than 0.6) were removed. 0.6 was visually detected by intra-brain synchrony distribution. Top highest 10 intra-brain synchronizations are displayed. Inter-brain synchronization show the similar pattern during co-operation and competition: the prefrontal and occipital lobes are highly activated. In competition, the prefrontal lobe is also connected with the frontal lobe. Inter-brain links between cooperation and competition also show similar patterns: the occipital and prefrontal lobes are connected with each other. During cooperation, INS also appeared between Pz and Oz. This brain map shows similar results with the Fig.4.4



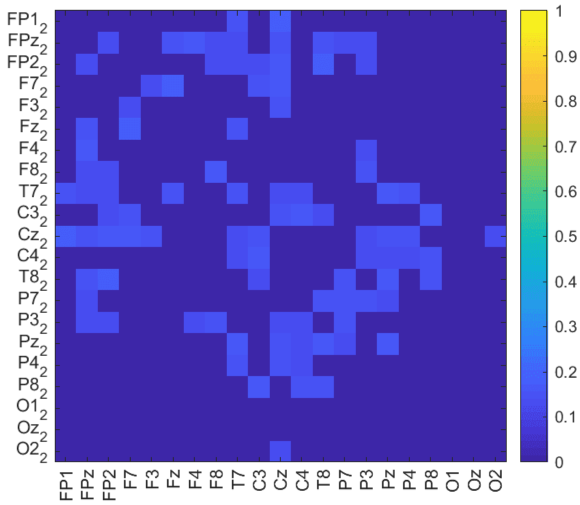
(a) Adjacency matrix of power-correlation-based intra-brain network during competitive interaction



(b) Adjacency matrix of power-correlation-based inter-brain network during competitive interaction

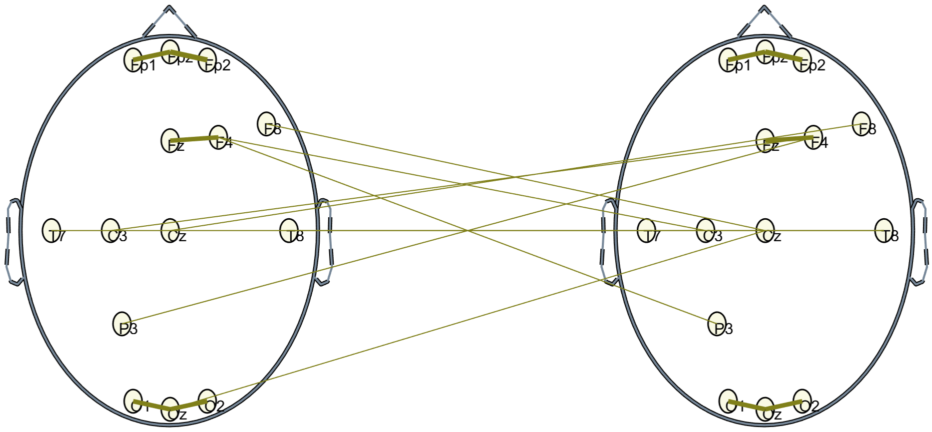


(c) Adjacency matrix of power-correlation-based intra-brain network during co-operational interaction

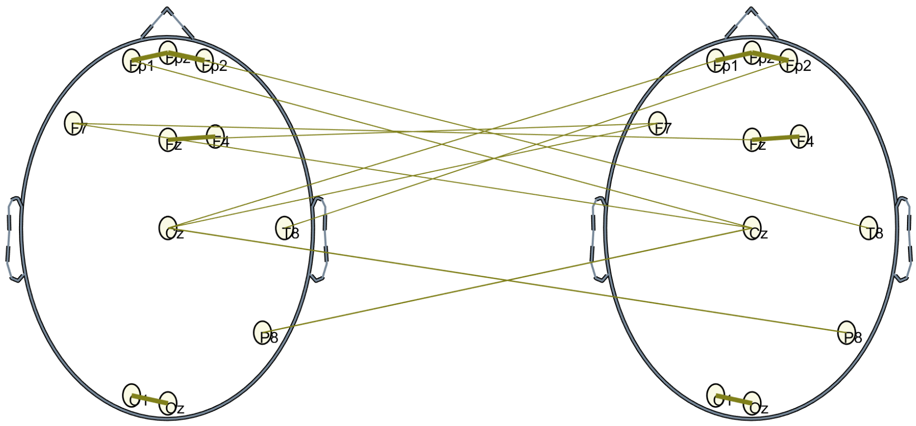


(d) Adjacency matrix of power-correlation-based inter-brain network during co-operational interaction

Figure 4.6: Adjacency matrix of power-correlation-based team brain network. Co-operation and competition have similar amount of intra-brain NS, while there are more INS one cooperation. Intra-brain NS is more strong than inter-brain NS. With regard to intra-brain NS, (a) and (c) show that signals at frontal lobe are highly synchronized with data at pre-frontal lobe. (c) illustrates that signals at parietal lobe lobe also synchronized with brain activities at prefrontal and frontal lobes. As for INS, (b) shows INS is scattered between nodes. (d) shows signal at central and parietal lobes are highly synchronized.

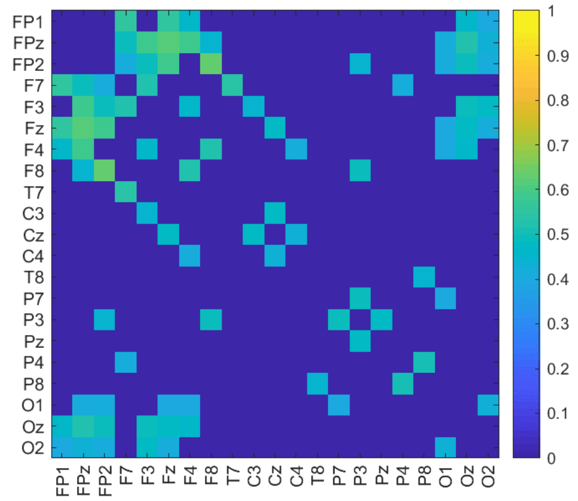


(a) The power-correlation-based team brain map during competitive interaction

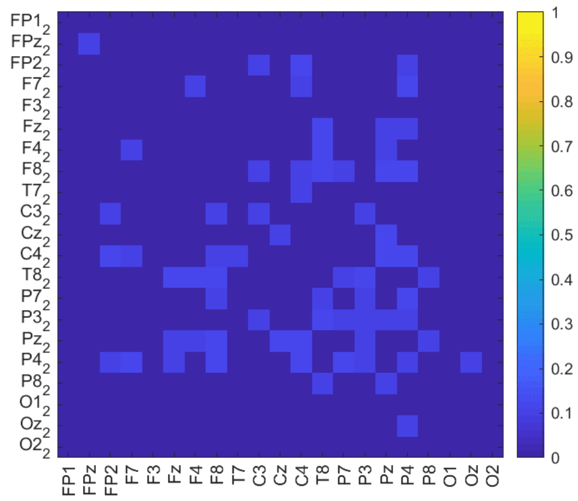


(b) The power-correlation-based team brain map during co-operational interaction

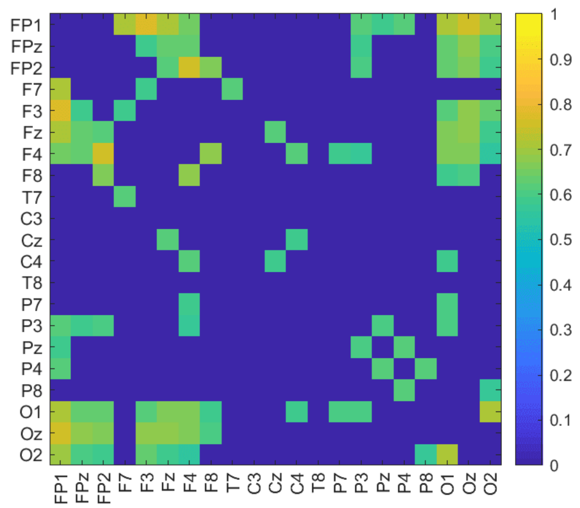
Figure 4.7: Team brain map of the power-correlation-based team brain networks. Line thickness indicates neural synchrony strength. Within-brain lines represent intra-brain synchronizations while inter-brain lines represent inter-brain synchronization. Intra-brain NS with lower power-correlation value (smaller than 0.6) were removed. 0.6 was visually detected by intra-brain synchrony distribution. Top highest 10 intra-brain synchronizations are displayed. Intra-brain links show that the pre-frontal and occipital lobes are activated. Intra-brain connection also appeared between Fz and F4. Inte-brain links on competition show that the left central lobe is connected with the right frontal lobe. Cooperative INS show the frontal lobe is connected with the other brain's right central and right frontal lobes. Although all connections in this plot do appear in Fig.4.6, Fig.4.6 shows more patterns that do not appeared in this brain map :intra-brain shows that the prefrontal and occipital lobes connected with each other; cooperative INS show that the parietal lobe connects with the central the parietal lobes.



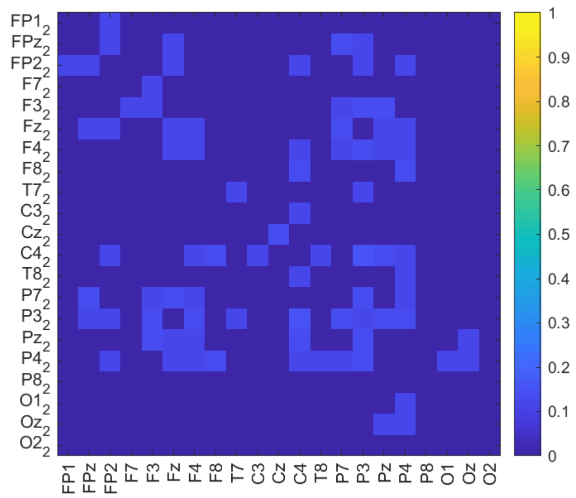
(a) Adjacency matrix of the spectral-coherence-based intra-brain network during competitive interaction



(b) Adjacency matrix of the spectral-coherence-based inter-brain network during competitive interaction

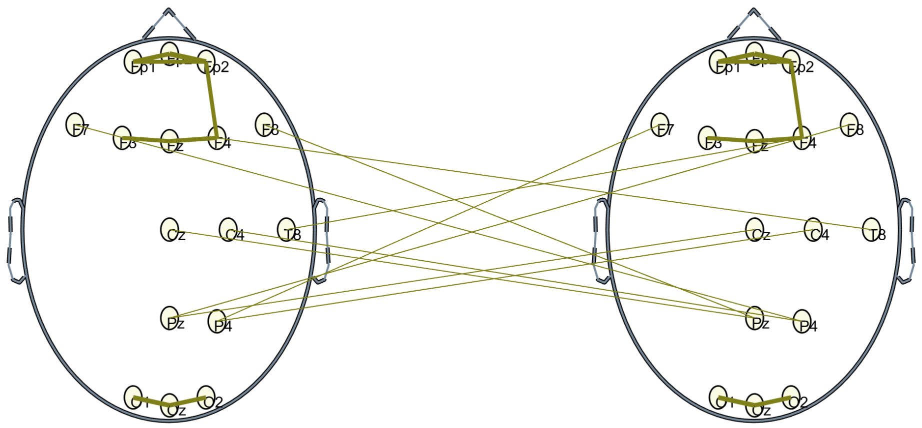


(c) Adjacency matrix of the spectral-coherence-based intra-brain network during co-operational interaction

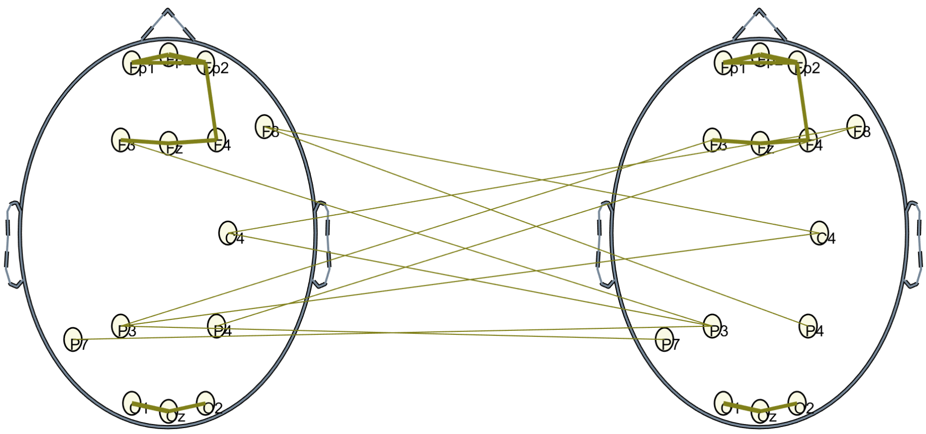


(d) Adjacency matrix of the spectral-coherence-based inter-brain network during co-operational interaction

Figure 4.8: Adjacency matrix of spectral-coherence-based team brain network. Co-operation(c) has more intra-brain NS and they are more strong as compared with competition(a). Intra-brain NS show that the frontal and occipital lobes are highly activated; INS indicates that the parietal lobe is strongly activated.



(a) The spectral-coherence-based team brain map during competitive interaction



(b) The spectral-coherence-based team brain map during cooperative interaction

Figure 4.9: Team brain map on spectral-coherence-based team brain network. Line thickness indicates neural synchrony strength. Within-brain lines represent intra-brain synchronizations while inter-brain lines represent inter-brain synchronization. Intra-brain NS with lower power-correlation value (smaller than 0.45) were removed. 0.45 was visually detected by intra-brain synchrony distribution. Top highest 10 intra-brain synchronizations are displayed. Intra-brain NS show similar patterns during cooperation and competition: the prefrontal, frontal and occipital lobes are activated; F4 connects with Fp2. Cooperative INS shows that more brain areas on the parietal lobe is activated as compared with competitive INS, which show that the right central lobe is activated. This plot shows a slightly different results with the Fig.4.8, where intra-brain NS show the frontal-lobe and parietal lobes does not connected with themselves, instead they connected with each other; intra-brain NS also show the frontal lobe connected with the prefrontal and occipital lobes while this plot does not show this pattern; INS in Fig.4.8 shows that the parietal is nearly synchronized with the other whole brain, while this pattern does not appeared in this brain map.

In the brain map,the EEG electrodes of two subjects are shown on the brain schematics by yellow dots on the left brain and right brain respectively. The lines represent the functional synchrony between the cortical areas under those electrodes: within-brain lines indicate intra-brain NS while inter-brain lines represent inter-brain NS. Link thickness corresponds to neural synchrony value: thick lines indicate strong NS while thin links represent weak NS. Intra-brain NS are symmetrical in subjects since intra-brain NS are averaged over all trials (subjects). The threshold for intra-brain neural synchrony is visually decided by their distribution (Fig4.3a). Top 10 highest INS are chosen because of the INS distribution (Fig.4.3b). Fig.4.5, Fig.4.7, Fig.4.9 respectively show the brain-map of ISPC-, power-correlation- and spectral-coherence-based NS.

The summarization of brain maps of ISPC-, spectral-coherence- and power-correlation-based brain networks is shown in Tab.4.2.

FC method	Intra-brain networks	Inter-brain networks
ISPC	1. Pre-frontal, frontal and occipital lobes are highly activated during both cooperation and competition; 2. Cooperative and competition intra-brain networks have similar NS strength; 3. Strong competitive intra-brain NS appeared between the pre-frontal and frontal lobes.	1. Occipital and prefrontal lobes are highly synchronized with each other and themselves; 2. Similar synchronized pattern for cooperation and competition
Spectral-coherence	1. The same activation areas with ISPC; 2. cooperative intra-brain network has more strong NS	1. Competitive INS show that the right central lobe is highly activated 2. Cooperative INS show that more brain areas on the parietal lobe highly synchronized with the frontal lobe,
Power-correlation	1.Pre-frontal, frontal and occipital lobes are highly activated on cooperation and competition.	1. Competitive INS show that the left central lobe strongly synchronized with the right frontal lobe. 2. Cooperative INS show that the prefrontal lobe synchronized with the central lobe.

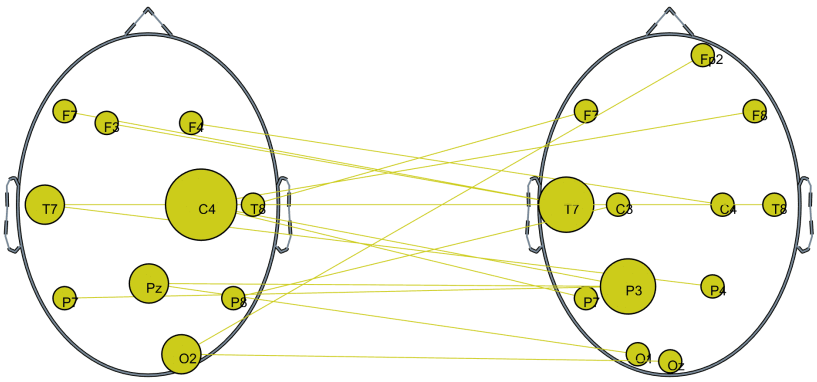
Table 4.2: Brief summarization of intra- and inter-brain networks based on ISPC, spectral-coherence and power-correlation methods.

4.3 Statistically Significant Inter-Brain Synchrony

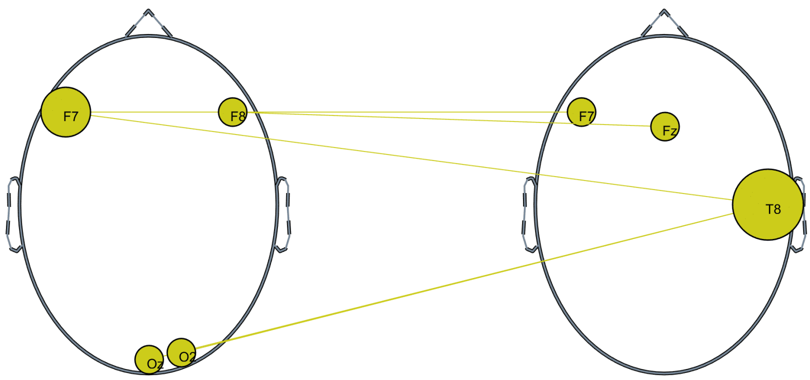
4.3.1 Brain maps of significant Inter-Brain Synchrony

For each INS pair, the permutation test with 500 shuffles was applied to find statistically significant INS pairs during cooperation as compared with competition. Fig.4.10a, Fig.4.10b respectively illustrate statistically significant INS on ISPC-, power-correlation-based team brain networks. The result based on spectral-coherence is shown in Appendix.A.1.3. The line between two brain represents one statistically significant INS. Node represent electrode. Node that have more links (more statistically significant INSs) are larger.

Results show that statistically significant INS is different among NS measurements. All p-values of these statistically significant INS are zero.



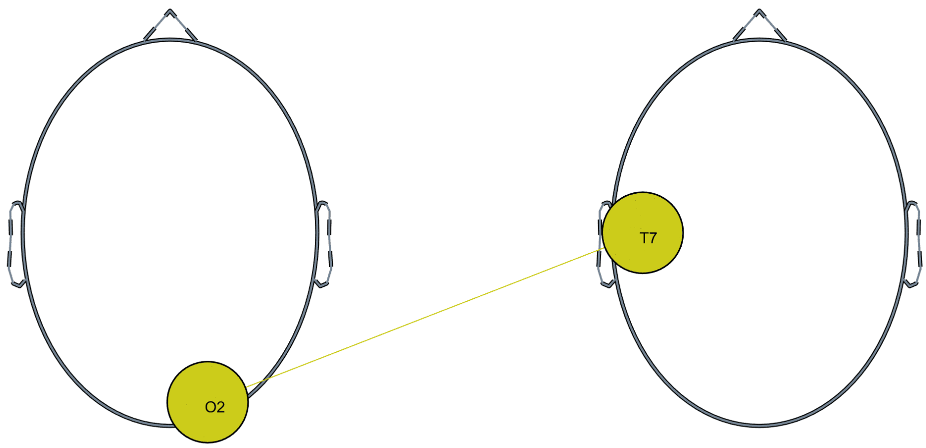
(a) Statistically significant ISPC-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. C4 and T7, P3 are three biggest nodes.



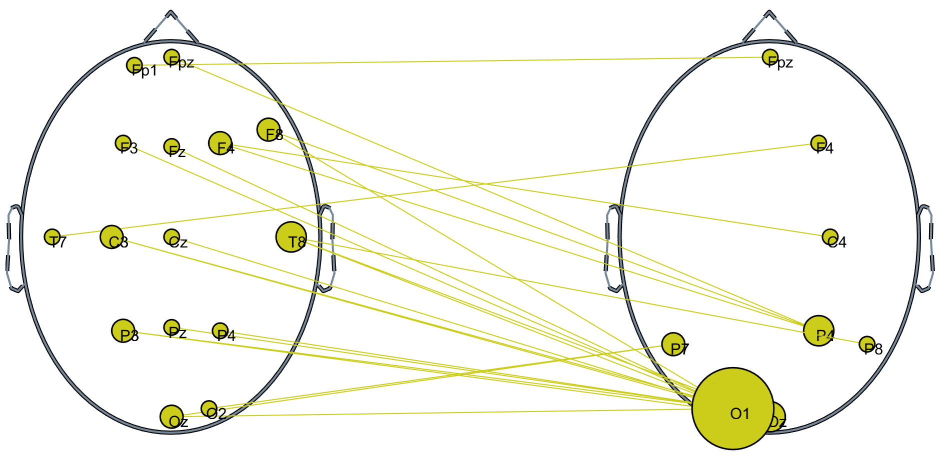
(b) Statistically significant power-correlation-based INS are illustrated for cooperation vs. competition. F7 and T8 are two biggest nodes.

4.3.2 Significant Inter-Brain Synchrony on Different Time-range/Brain-waves

To inspect weather significant INS are stable over different frequency bands, statistically significant INS on alpha wave were calculated and shown in Fig.4.10d. The results show that statistically significant INS is totally different on different frequency bands.



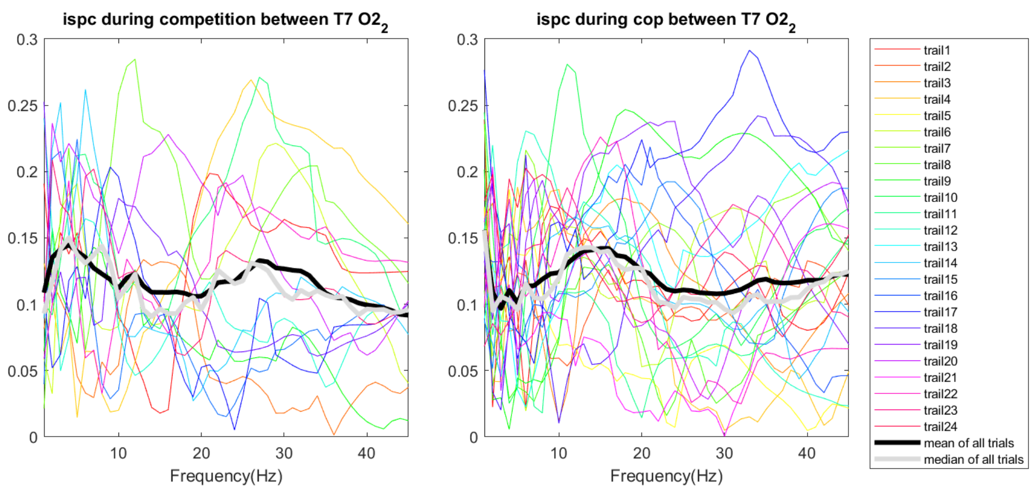
(c) Statistically significant ISPC-based INS during cooperation and competition on beta frequency band. It was calculated based on the last 15-seconds of the data.



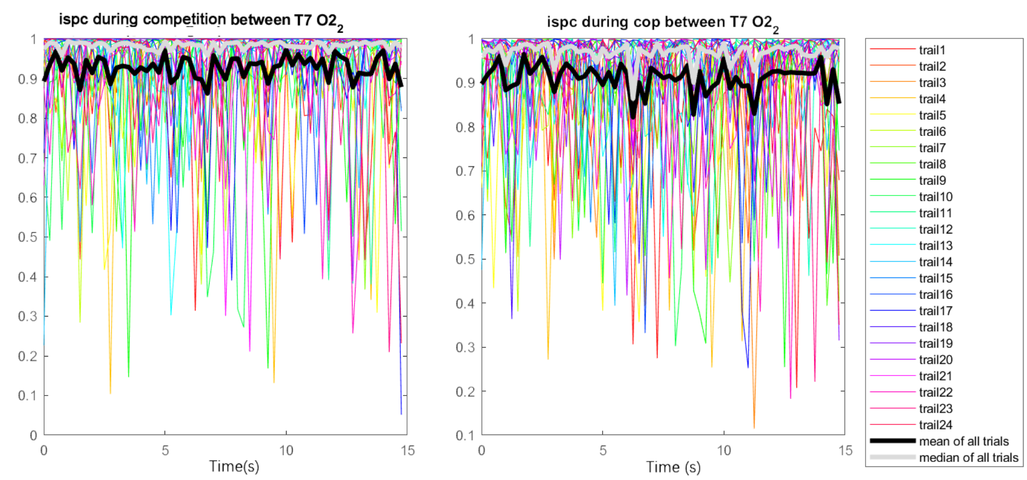
(d) Statistically significant power-correlation-based INS during cooperation and competition on alpha frequency band. It was calculated based on the last 15-seconds of the data.

Figure 4.10: Statistically significant power-correlation-based INS on alpha and beta brain waves.

4.3.3 Significant Inter-brain Synchrony over frequency and time



(a) ISPC-based INS between T7 and O2 during cooperation and competition over frequency. The left panel shows the competition while the right shows the cooperation. X-axis shows frequency, which ranges from 0 to 45; y-axis indicates ISPC strength. Each line represents a trial, as shown in the legend. The black line represents the mean value over all trials while the gray line represents the median value. The black lines on cooperation and competition slightly fluctuate around 0.1. Notably, the ISPC value range from 0 to 0.3. As compared with Fig.4.11b, where y-axis ranges from 0 to 1, this INS is relatively stable over frequency.



(b) ISPC-based INS between T7 and O2 during cooperation and competition over time. The left panel shows the competition while the right shows the cooperation. X-axis show the time, ranges from 0 to 15 seconds, y-axis show this INS strength. Each line represents a trial, as shown in the right legend. The black line represents the mean value over all trials while the gray line represents the median value. Notably, the ISPC value range from 0 to 1 and ISPC fluctuates dramatically over time. However, the mean value on two conditions behave quite similar over time: slightly fluctuate around 0.9.

Figure 4.11: Line plot of ISPC-based T7-O2 INS over time and frequency

Fig.4.10c shows INS between T7 and O2 is the statistically significant INS during cooperation and competition, which means the mean INS over cooperative trials is different with the mean INS over competitive trials.

To exploratory inspect this difference over time or frequency, Fig.4.11a and Fig.4.11b respectively illustrate this INS over frequency and time. The mean INSs between two conditions (which shown in black line in Fig.4.11a and Fig.4.11b) do not show strong difference.

4.4 Inter-brain Synchrony over frequency

Because INS is relatively stable over frequency (as shown in Fig.4.11a), INS on competition is compared with INS on cooperation over frequency. Box-plot of INS on different condition over frequency is shown in Fig.4.12. Results show that INS during cooperation is slightly strong as compared with INS on competition.

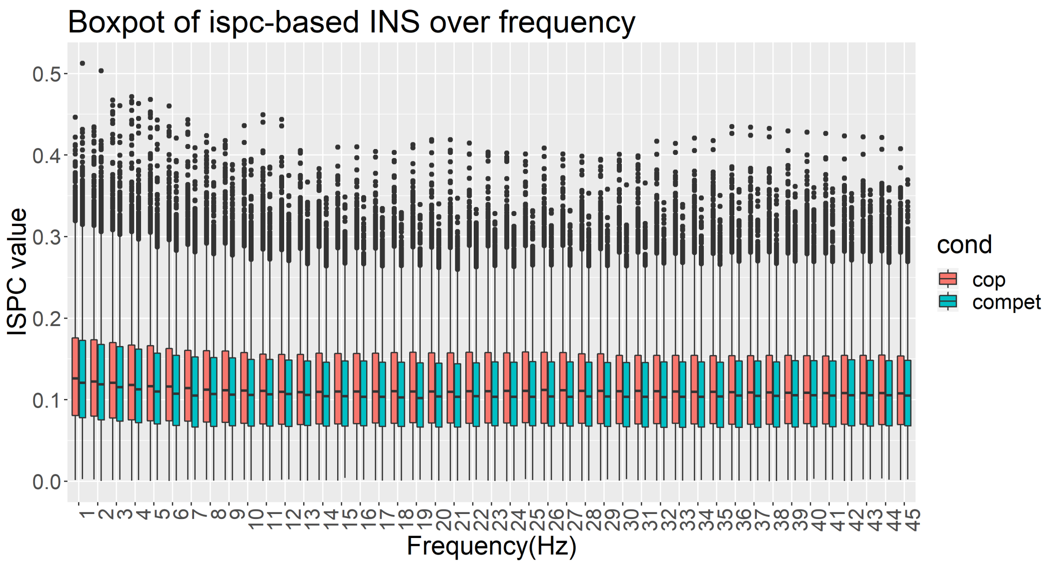


Figure 4.12: ISPC-based INS over frequency. X-axis represent frequency (from 1 to 45Hz) while y-axis shows ISPC-value. INS on cooperation is shown in red while INS on competition is shown in green, as shown in the right legend. This plot is based on the last-15-seconds data. INS on cooperation is slightly higher than INS on competition; INS have the same distribution on cooperation and competition.

4.5 Behavioral Data

4.5.1 Team-Performance and Inter-Brain Synchrony

Team performance was quantified by game duration: long game duration implies bad team performance.

Fig.4.13 illustrates the scatter-plot between game-duration and PLI-based INS. More scatter-plots based on other FC methods can be found in App.A.1.4. Results show that INS is not correlated with game-performance.

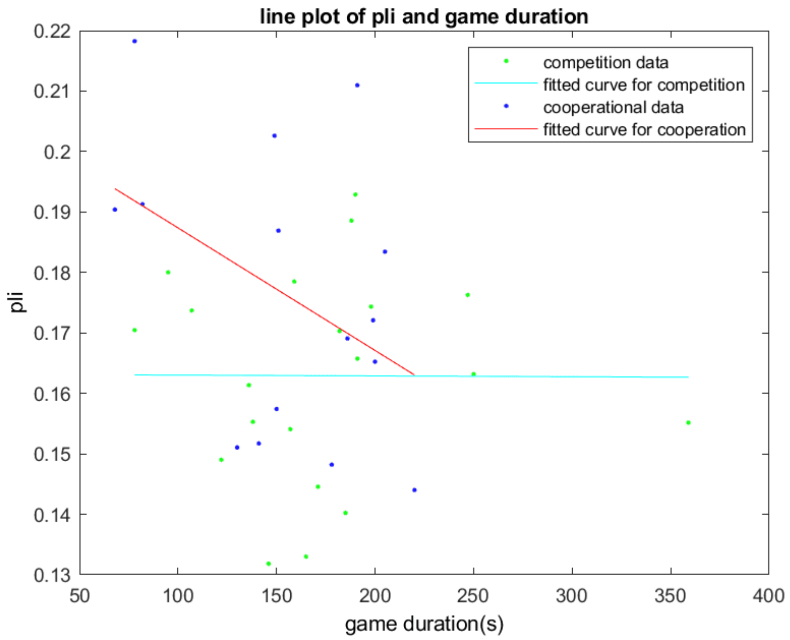


Figure 4.13: Scatter-plot between game-duration and PLI-based INS. Team-performance is quantified by game-duration. X-axis shows the game duration in seconds; y-axis show the INS strength. Each dot represents a trial: green dots represent cooperative trials while competitive trials are shown in blue dots. The line donates the best linear fit between predicted and original values. There is no strong relationship between INS and game duration as dots are not tightly attached around lines.

4.5.2 Team-Performance and Global Efficiency

Fig.4.14 shows how team-performance is related with GE of power-correlation-based team brain network. The results based on other FC methods can be found in Appendix.A.1.4. Results show that team-performance does not relate with GE.

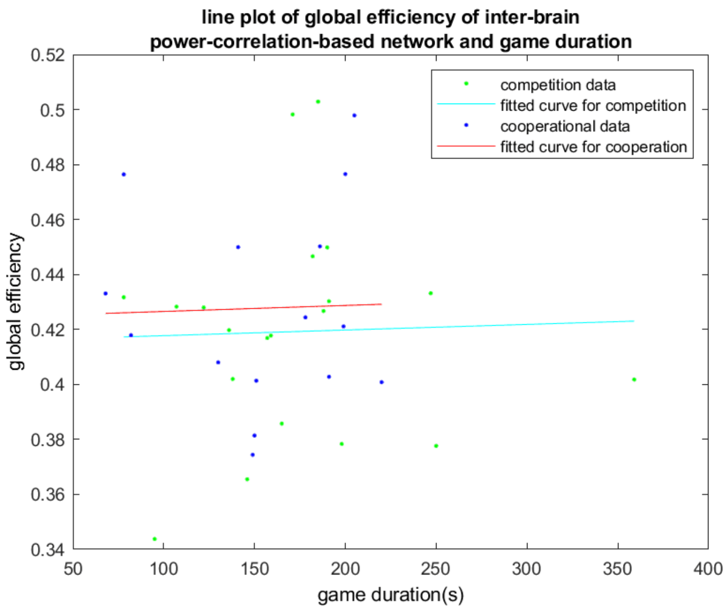


Figure 4.14: Scatter-plot between game duration and the GE of team brain network. Team-performance is quantified by game duration in seconds. Each dot represents a trial: green dots represent cooperative trials;blue dots represent competition trails; The line denote the best linear fit between predicted and original values: blue line denotes the best linear fit on competitive data while the green line is based on the cooperative data. The relationship between the game duration and GE of the team-brain network is very weak.

4.6 Topological Properties of Networks

Three topological properties were calculated: SWN, GE and betweenness centrality.

4.6.1 Global Efficiency

	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.3994	0.3982	0.6716	0.4867
Power-correlation	0.2572	0.2469	0.5761	0.3168
Spectral-coherence	0.2076	0.1998	0.7482	0.3024

Table 4.3: GE of team- and intra-brain networks on averaged-1-second data

Tab.4.3shows the global efficiency of team- and intra-brain networks during co-operational and competitive interaction. GE results on the last 30 and 15 seconds of data can be found in Tab.A.3 and Tab.A.1. Based on these three tables, findings are listed in Tab.4.4.

Facts	Findings
GE of intra-brain network is higher than GE of team-brain networks	Individual brain exchange information more efficient than team-brains
GE of competitive intra-brain network is higher than GE of cooperative intra-brain network	individual brain exchange information more efficient on competition than cooperation
GE of competitive and cooperative team-brain are similar	Cooperative and competitive team-brain network exchange information with similar efficiency

Table 4.4: Findings based on GE of intra- and team-brain networks

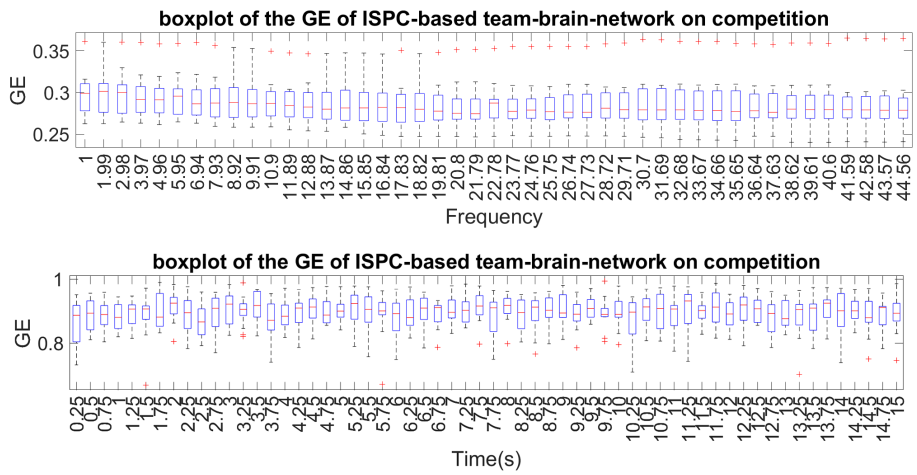


Figure 4.15: Box-plot of GE of ISPC-based team-brain network over time and frequency. The upper plot shows GE over frequency while the lower plot indicate GE over time. X-axis in the upper plot represent frequency, which ranges from 0 to 45Hz; while x-axis in the lower plot represent time, range from 0 to 15 seconds. Y-axis shows GE value. Notably, the upper plot shows that GE over frequency ranges from 0.25 to 0.35; while the lower plot shows that GE over time ranges from 0 to 1, which indicates that GE is unstable over time and stable over frequency. GE over time is overall higher than GE over frequency.

To inspect weather GE of the team brain network is stable over time and frequency, Fig.4.15 shows GE of ISPC-based team brain network over time and frequency This figure indicates that GE is unstable over time while stable over frequency.

4.6.2 Small-world-ness

Small world coefficient measures how the network acts as functionally integrated network. Small-world networks are featured by high clustering coefficient and low shortest path. Tab.4.5 illustrates SWN of team- and intra-brain networks on averaged-1-second data, the corresponding results on the last 15 and 30 data are respectively shown in AppendixA.2.4. and Appendix.A.3.4.

Intra-brain networks on cooperation have a slightly large SWN as compared with competition. Low GE and high SWN of the intra-brain network on cooperation indicates this network is highly clustered. Differently, SWN of team-brain networks change over time and FC methods: there is no common pattern in SWN of team-brain networks on averaged-1-second data, the last 15 and 30 seconds data.

	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.8670	0.8661	0.8944	0.8972
Power-correlation	1.2006	1.2227	0.8921	0.9125
Spectral-coherence	1.2378	1.1945	0.9041	1.0923

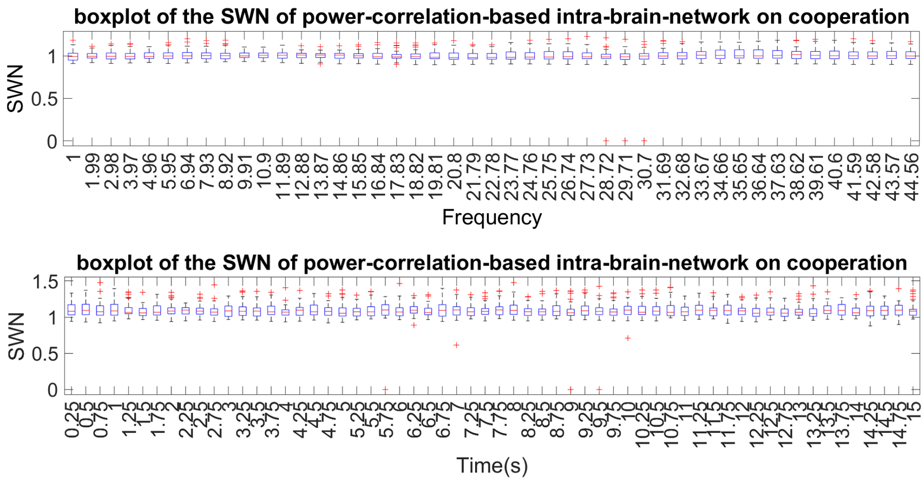
Table 4.5: SWN of team- and intra-brain networks during cooperation and competition on averaged-1-second data

Combined with GE, findings based on SWN are shown in Tab.4.6.

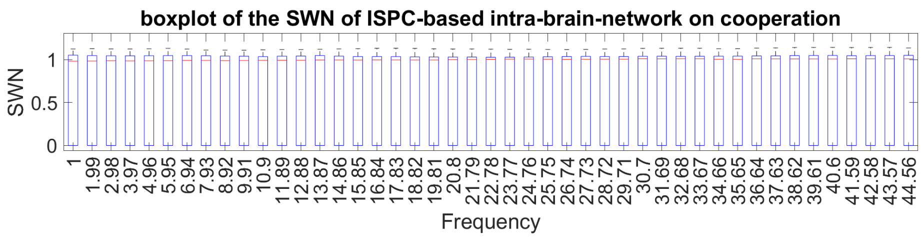
Facts of SWN	Combined with Facts of GE	Findings
SWN of cooperative intra-bran network is slightly larger than SWN of competitive intra-brain networks	GE of cooperative intra-brain network is smaller than GE of competitive intra-brain networks	There are more cluster in cooperative intra-brain network as compared with competitive intra-brain network
SWN of team-brain network is similar with SWN of intra-brain networks	GE of team-brain networks is way smaller than GE of intra-brain networks	There are more clusters in team-brain networks as compared with intra-brain networks

Table 4.6: Findings based on SWN and GE

To inspect weather SWN stable over time and frequency, Fig.4.16a show SWN of cooperative power-correlation-based intra-brain network over frequency and time. SWN of power-correlation-based network can be found in Appendix.A.2.5. Results indicate that SWN is stable over time and frequency. SWN variances are heavily dependent on neural synchrony measurements. Fig.4.16b shows SWN of cooperative ISPC-based intra-brain network over frequency.



(a) SWN of power-correlation-based cooperative intra-brain network over frequency and time. The upper plot shows SWN over frequency while the lower shows SWN over time. X-axis in the upper plot shows frequency, which ranges from 0 to 45Hz; x-axis in the lower plot shows the time, which ranges from 0 to 15 seconds. Y-axis represent SWN. SWN is stable over time and frequency.



(b) SWN of cooperative ISPC-based intra-brain network over frequency. Compared with Fig.4.16a-SWN of power-correlation-based brain networks, SWN of ISPC-based brain network has large variance as compared with SWN of power-correlation-based brain network.

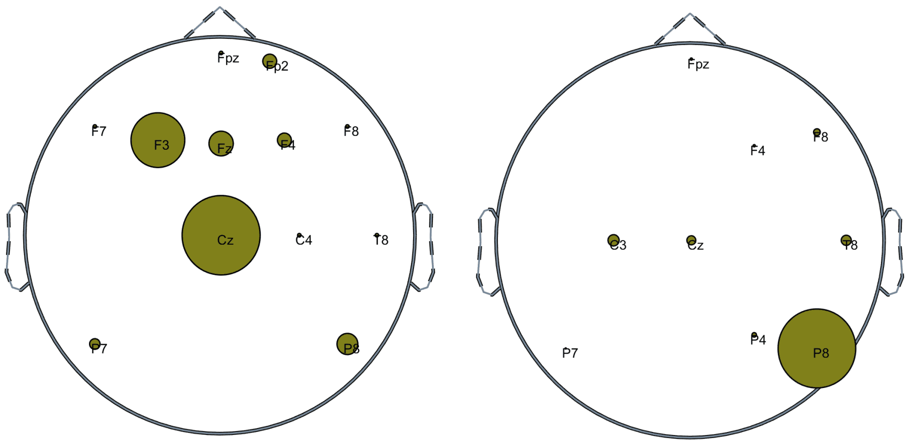
Figure 4.16: Boxplot of SWN over time/frequency and on different FC methods.

The stability of GE and SWN over time and frequency is summarized in Tab.4.7

	Over frequency	Over time	Notes
GE	relative stable	relative unstable	GE over time is larger as compared GE over frequency

SWN	Relative stable	Relative unstable	1. Variance of SWN depends on FC method 2. SWN (based on median FC value of all trials) over frequency is larger than SWN over time

Table 4.7: Stability of SWN over frequency and time



(a) Hubs of the ISPC-based team brain network during competition

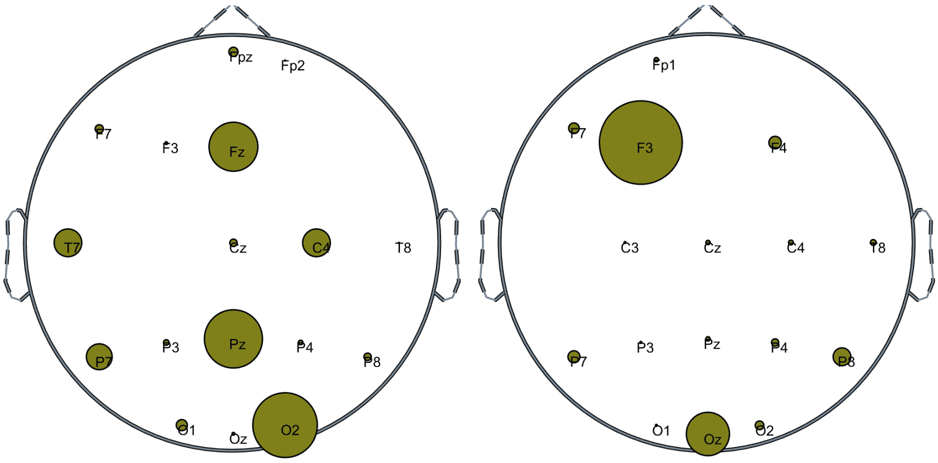
(b) Hubs of the ISPC-based team brain network during cooperation

Figure 4.17: Illustration of hubs of ISPC-based team brain network on cooperative/-competitive interaction. Hubs were measured by betweenness centrality. Nodes that without zero betweenness centrality in the team brain networks are displayed. Node side corresponds to betweenness centrality value: big size means high centrality. Cz,F3 in (a) and P8 in (b) are most important electrodes in information exchange of the ISPC-based team brain networks during competition and cooperation respectively.

4.6.3 Betweenness centrality

Betweenness centrality is a way of detecting the amount of influence an electrode has over the flow of information in a brain network. It is often used to find electrodes that serve as a bridge from one part of a brain network to another. Fig.4.17, Fig.4.18 respectively illustrate brain hubs of ISPC- and power-correlation-based team brain networks on cooperative/competitive interaction. Brain hubs on spectral-coherence is shown in Appendix.A.1.5. Notably, there is no hubs in PLI- and MI-based networks. Hubs on the last 15 and 30 seconds of data are shown in Appendix.A.2.3 and Appendix.A.3.3.

All results show that hubs are dynamic over time and neural synchrony measurements.



(a) Hubs of the power-correlation-based team brain network during competition

(b) Hubs of the power-correlation-based team brain network during cooperation

Figure 4.18: Illustration of hubs of power-correlation-based team brain network on cooperative/competitive interaction. Fz,Pz and Oz in (a) and F3,Oz in (b) are most important electrodes in information exchange of the power-correlation-based team brain networks during competition and cooperation respectively.

Chapter 5

Discussion

The present study was designed to analyze neural-dynamics in cooperation and competition with EEG.

5.1 Robust of Different Inter-Brain Synchrony

The first research task is to analyze to what extent FC methods are robust to white noise.

The results, as shown in Fig.4.2, revealed that MI is very sensitive to noise, power is the least sensitive measurement. ISPC-based and spectral-coherence-based NS somewhat have the similar sensitive level to Gaussian noise and this is maybe because spectral coherence is power-weighted ISPC.

PLI is robust to volume conduction. Interestingly, PLI is zero when measure weather clean data is synchronized with itself. Zero PLI is explained into non-synchronization, and this is counter-intuitive since clean data should be perfectly synchronized with itself. The theoretical meaning of zero PLI is zero-phase-lag between two signals, which is abnormal in neural data and could be caused by volume conduction. This shows that although PLI is robust to volume conduction, PLI can miss some significant NS.

Another important finding is that all FC methods lose power to quantify NS if data is heavily contaminated by noise.

Previous studies found normal SNR of EEG is below than 1, but the SNR were computed as the ratio of ongoing brain activity to the amplitudes of blink related potentials [69]. Another paper showed that normal SNR of EEG was mainly between 4 and 6, while SNR was measured as the root mean square (RMS) value of the measured signal divided by the RMS noise level [70]. Based on different SNR calculation methods, it is hard to compare our results with these previous studies.

The limitation of our method is the noise source. In our method, white noise

(Gaussian noise) is added in the clean signal while in EEG signals, noise artifacts are strong deviated from Gaussian distribution [71]. This fact leads to our findings are less valid and practical.

5.2 Neural Synchrony between Cooperation and Competition

The second research task is to analyze NS during cooperative and competitive interaction, which can be tackled in two ways: (1) finding statistically significant INS between cooperation and competition (2) finding strong intra- and inter-brain NS.

5.2.1 Statistically Significant Inter-Brain Synchrony

Results show the mean INS between cooperation and competition are different for all NS measurements. However, no consistent pattern was found during all these NS measurements. Furthermore, statistically significant INS changes over time-range and frequency waves.

This is probably because INS is slightly unstable over frequency and dramatically unstable over time. This instability makes these statistically significant INS are less valid. Different with permutation methods,Nishant Sinha at al. [46] applied nonparametric methods (wilcoxon signed-rank test) to test whether the median of each INS pair is the same between cooperation and competition. They found statistically significant INS is unstable over frequency-band. However, their results are less valid: (1) they only calculated one NS measurement; (2) power correlation based on the Pearson correlation coefficient without normality check.

One statistically significant INS is further checked over frequency (Fig.4.11a) and time (Fig.4.11b). Results show that this INS is unstable over frequency and fluctuate dramatically over time. Further, the median of this statistically significant INS (shown in black line in Fig.4.11a and Fig.4.11b) is slightly similar between cooperation and competition regardless of time or frequency. They do not differ with each other a lot over time or frequency, this fact further proves that our statistically significant INSs are doubtful.

5.2.2 Strong Neural Synchrony

As for intra-brain synchrony, ISPC, spectral coherence and power-correlation show similar patterns over time: frontopolar (Dorsolateral Frontal Cortex (DLFC)) and parastriate (a.k.a secondary visual cortex) are highly activated. DLFC activation is consistent with previous studies: Baker, Joseph M et al. [64] found significant activation in the right frontopolar; the coherence between signals generated by participants' right superior frontal cortices increased during cooperation [26]; parent's and child's brain activities synchronized in the dorsolateral prefrontal and frontopolar cortex during cooperation [27];lover dyads demonstrated increased INS in right superior frontal cortex [68]. While parastriate involvement maybe due to its functionality: it is responsible for interpreting images.

Activation in the right superior frontal cortex during a cooperative game rather than competition was explained merely by the similarities in action [26]. Activation in the left prefrontal cortical also relates with personality traits: highly motivated person show strong activation [2]. Further, prefrontal area activation was founded in many social-interaction studies. In lieu thereof, INS in prefrontal brain areas might be a neural mechanism which sub-serves social interaction [72].

Different with intra-brain NS, there is no consistent pattern among strong INS: it changes over time-range and on NS measurements. Power-correlation- and spectral-coherence-based INS show slightly similar patterns. This is maybe because spectral-coherence is weighted by power as shown in Formula.2.2.

Intra-brain NS are much more strong than inter-brain NS, which is intuitive as the brain is more synchronized within itself rather than with the other brain.

5.3 Inter-Brain Synchrony over Frequency

INS on cooperation is slightly stronger than INS on competition, as shown in Fig.4.12 (and Fig.A.1).

Nishant Sinha et al. [46] also found that INS during cooperation was much stronger than INS during competitive interaction. Differently, Nishant Sinha et al. [46] only calculated all statistically significant INS between two conditions, while we also include all non-statistically significant INS. Further, Nishant Sinha et al. [46] segmented data into 1 second without any overlapping, we tested results on two different time slice methods: 1 second epoch with .5s overlapping; the last 15 seconds.

Another study [73] also found that inter-brain synchronizations are much denser in cooperation as compared with defection. In this study, partial directed coherence was applied. They applied t-test to find statistically significant INS between rest-state and cooperation/competition. They found the pattern of inter-subject connectivity in the cooperation condition is denser than in the defect case. During the rest state, subjects were in the same experience setting without any human interaction (they just watch the images in Prisoners Dilemma game without cooperating/competing with the other).

5.4 Team-Performance and Neurodynamics

The third research task is to find how team-performance relates with INS and GE of the team brain network.

INS does not relate with team-performance, which is against the previous findings [26] [74] [29]: increased coherence was associated with better cooperation performance.

There are some possible explanations: (1) our game difficulty changes over time, this is different with most experiments in other papers, where difficulty remain the same during experiments; (2) limited trials were analyzed; (3) game duration can not perfectly quantify team-performance.

Further, previous studies [26] [74] only calculated the INS pair between the same electrodes (s.t., two Fp1 electrode between two brains) instead all possible INS pairs, which were analyzed in our method. Different methodology may lead to different results. Caroline Szymanski et al. [29] fund that phase synchronization correlates with behavioral team performance. But they conducted a simple visual searching task without any changing difficulty. They also use reaction time instead game duration to quantify team-performance.

5.5 Topological Properties

This study set out with the aim of explaining team neurodynamics in graph theory perspective.In this research,three topological properties were calculated: GE,SWN and betweenness centrality.

Global Efficiency

In the network theory, GE measures how efficient a network exchanges information, and is quantified by the average inverse shortest path length in the network.

Results show that intra-brain network exchanges information more efficient as compared with team-brain network and it is intuitive. Competitive intra-brain networks exchange information more efficient than the cooperative intra-brain network.

Small-World-Ness

Small-world networks are featured by the small shortest path length and high clustering coefficient. SWN of intra- and inter-brain have similar values, while GE shows that intra-brain network have more smaller shortest path length (high GE), this fact indicates that there are more clusters in team-brain network.

Intra-brain network has similar SWN on competition and cooperation, while GE shows that competitive intra-brain networks have higher GE as compared with cooperative network (which means competitive intra-brain network have much smaller shortest path length). These facts indicate that cooperative intra-brain networks have more clusters as compared with competitive intra-brain networks.

SWN is unstable over NS measurements, as shown in Fig.4.16. There are another two ways of defining SWN, as discussed in Sec2.4.2. Different definitions may lead to different results.

Betweenness

Nodes with high betweenness may have considerable influence within a network by virtue of their control over information passing between others. Betweenness for MI-based team networks are zero, which means electrodes are all directly connected with each other.

Brain hubs are defined by betweenness centrality in this research, beside many other definition of centrality (s.t. based on nodes or page-rank centrality), hubs can also be defined as the nodes that connected two different communities.

Brain hubs changes over time, as the results show that brain hubs are totally different on different time-slots. Besides, based on different hubs definition, it is hard to find some consistent patterns during all different methods and over time.

Another obstacle is that the underlying neural theorems of these dynamic brain hubs are still remained to be explained. Until now, some papers found that it can reveal some dysfunction in cognitive-impaired brains (s.t. schizophrenia [75]). Another paper stated that hubs are central in brain communication and neural integration [22]. However, the underlying neural theories are still vague.

5.6 Limitation

There are many limitations in this study.

With regard to experiment, weather the pong-game can successfully elicit cooperative and competitive pattern between subjects is doubtful. Cooperation and competition are two common and opposite human interaction models, in which subjects respectively facilitate and obstruct others' goal achievement [2]. However, the pong-game in this study did not require high level cooperation or competition: there are not many options for they to facilitate or obstruct the other's game performance.

In this study, only one arbitrary frequency band (beta) was applied based on previous studies [76] [77] [64]. However, consistent with our results, previous findings also showed phase-coherence-based INS across different frequencies behaves different ans can be attributed to a series of different processes (from perception to cognition) [78]. Some papers analysis INS over different frequency bands [78] [46] [2], some papers chosen frequency bands based on visual inspection of the data (s.t., time-frequency analysis) [26] [79] or previous studies(s.t. a reduction of alpha power in the left-frontal brain [1]). In this study, only one frequency band (beta) is chosen based on previous studies. However, more frequency bands or tailored frequency ranges (based on time-frequency results) need to be analyzed.

No baseline experiments were conducted in our method. However, to inspect neural activity during social interaction, most papers applied human to machine interaction as baseline to compare human to human interaction [80]. Some paper employed the same experiment setting without human interaction as baseline. For example, subject watched the images in Prisoners Dilemma game without any interacting [73]. Baseline experiments were not conducted in our research, therefore, neural patterns maybe existed at first, instead of being elicited by cooperative and competitive interaction.

Topological properties were calculated on large-scale (data were averaged over time and frequency) rather than time-scale or frequency-scale. However, as results shown, NS are unstable over frequency and fluctuate over time.

Another limitations remains on the various definitions of the topological properties. For example, as discussed in Sec.2.4.2 and Sec.2.4.2, there are three ways of defining SWN, brain hubs can also be explained by different centrality (s.t. degree centrality or page-rank centrality) and by the nodes that connected different communities. Until now, there is no optimal definition. Different definitions lead to different results. However, this research only considered one arbitrary definition, which could generate biased and insufficient results.

The small amount of subjects in our experiment is also a limitation of this study. Only 9 dyads(18 persons) joined the experiment. Since each person may have totally different neural activities, it is hard to find some common neural patterns based on such a small dataset.

Another limitation is about the subject populations. Cognition is related with the age. In most papers, the age deviation of participants is quite small. However, in this research, the age of subjects ranges a lot. Intimacy also influence INS, for example, lovers have more strong INS as compared with strangers [68]. However, in this study, some groups are acquaintance instead of close friends.

Constrained by the experiment location, there are many background noise during experiment, which would distract subjects and could impair INS.

Chapter 6

Conclusions and Recommendations

6.1 Conclusion

This study set out to analyze team neurodynamics during cooperative and competitive interaction with EEG in four directions: (1) analyzing to what extent that different neural synchronization measurements are robust to the noise; (2) analyzing team neurodynamics based on different NS measurements (3) explaining NS in graph theory (4) relating team neurodynamics with team performance.

The results show that: (1) Concerning robust of neural synchrony measurements, MI is very sensitive to noise, Power-correlation is the least noise-sensitive NS measurement, PLI can lose some significant NS, ISPC and spectral-coherence have similar sensitivity to white noise; (2) Intra-brain neural synchronization shows prefrontal and parastriatel were highly activated on cooperation and competition; (3) NS is unstable over frequency and fluctuate dramatically over time; (4) INS on cooperation is slightly stronger than INS on competition; (5) INS does not highly correlate with team-performance; (6) Intra-brain network exchange information more efficient than team-brain network; (7) Individual brain exchanges information more efficient on competition as compared with cooperation; (8) Individual brain network has more clusters on cooperation as compared with competition; (9) Team-brain network has more cluster as compared with individual-brain network; (10) Global efficiency and small-world-ness of brain networks are relatively unstable over time and relatively stable over frequency; (11) SWN of ISPC-based networks has large variance; (12) Brain hubs changes over time; (13) Statistically significant INS between cooperation and competition dynamically changes over time, frequency and different neural synchrony measurements.

6.2 Future work

As regard with the subject population, subjects could belong the similar population (better the youth) and dyads could be close friends. More subjects could be recruited to eliminate individual neural differences.

The experiment could be redesigned to imitate cooperation and competition better, since the pong-game did not necessarily require subjects to highly cooperate or complete with the other.

Data could be analyzed over time and frequency instead on the averaged data.

With regard to the brain networks, topological properties can be calculated on different definitions and to figure out common patterns during cooperation and competition.

Directed functional connectivity, such as Granger causality and transfer entropy, could be applied to explore directed influence of signal x on signal y.

Multilayer brain network could be generated based on different time-slots or different frequencies (which means each layer represents one time-slots/frequency). By linking brain regions (nodes) by their interactions (time- or frequency-dependent neural synchronization), nontrivial brain functional structure could be uncovered. Some multilayer-dependent topological properties(s.t., motif) could be calculated.

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Appendix A

Appendix

A.1 Results of 1-second-epoched data

A.1.1 Inter-Brain Synchrony over frequency

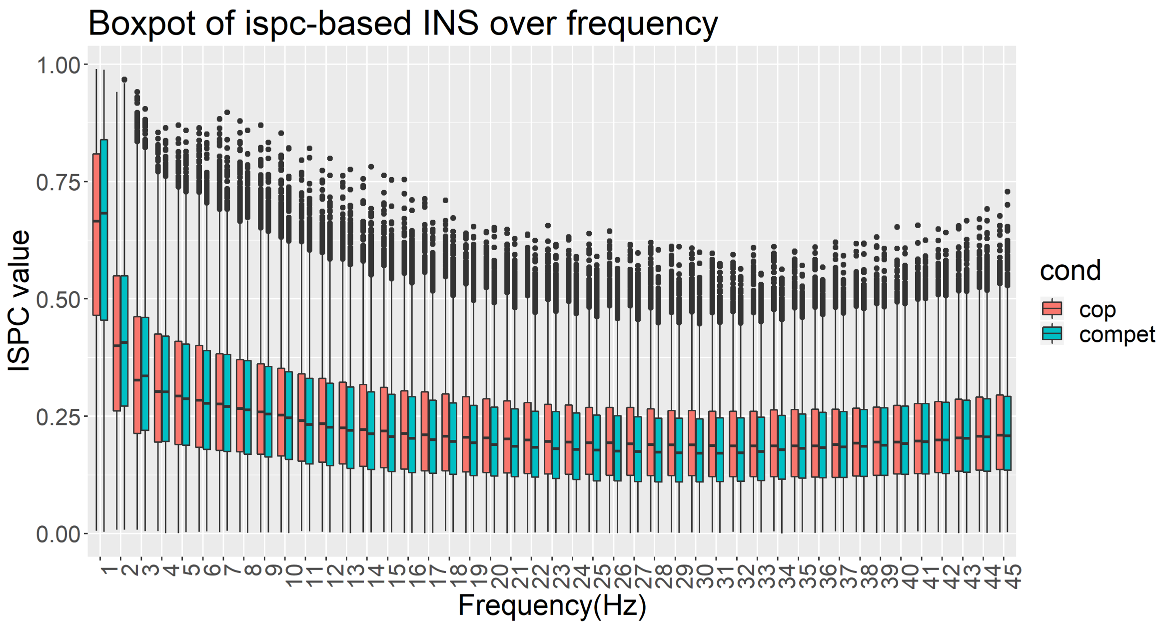
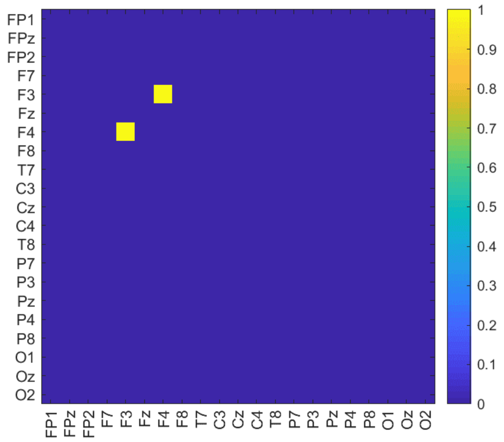


Figure A.1: ISPC-based INS over frequency. X-axis represent frequency (from 1 to 45Hz) while y-axis shows ISPC-value. This plot is based on 1-second-epoched data. cooperative INS are slightly higher with competitive INS over all frequency bands except delta and theta brain waves. This result is slightly different with the result based on the last 15 seconds of data(Fig.4.12), where INS on cooperation is slightly higher overall frequency bands (1-45Hz).

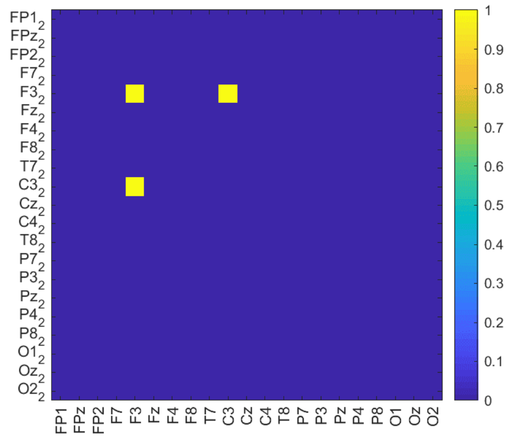
A.1.2 Strong Neural Synchrony

This section shows MI-based and PLI-based strong NS. Only one threshold was applied: one standard deviation above median of intra- and inter-brain NS.

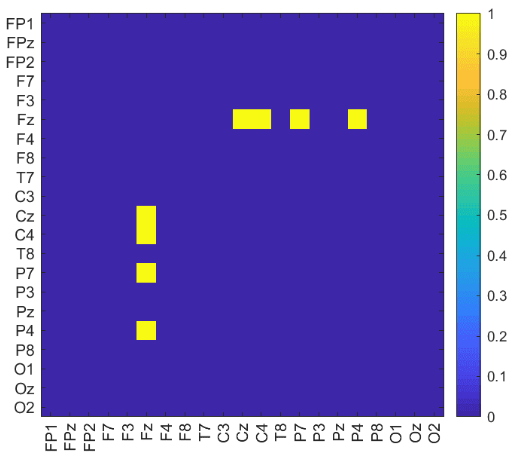
Fig.A.2 shows the adjacency matrix of MI-based intra- and inter-brain networks.



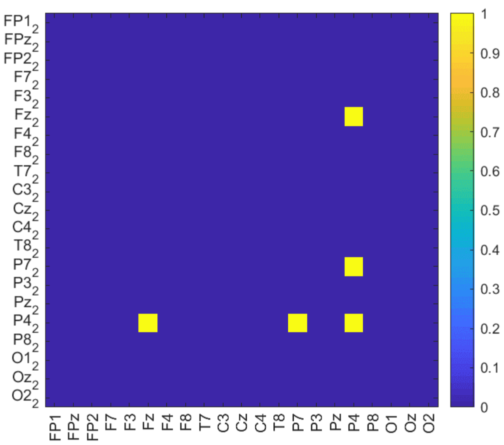
(a) Adjacency matrix of MI-based intra-brain network during competitive interaction



(b) Adjacency matrix of MI-based inter-brain network during competitive interaction



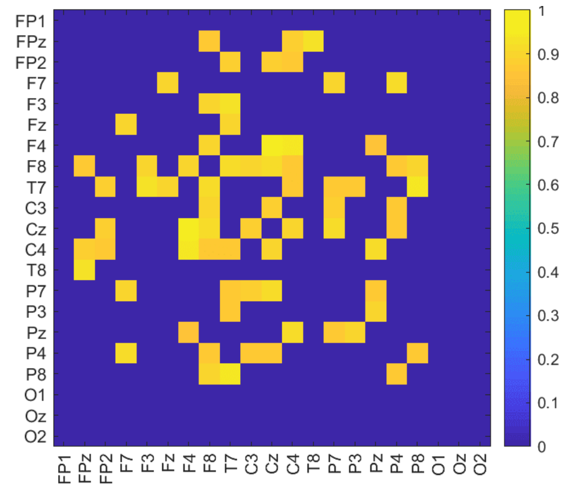
(c) Adjacency matrix of MI-based intra-brain network during cooperative interaction



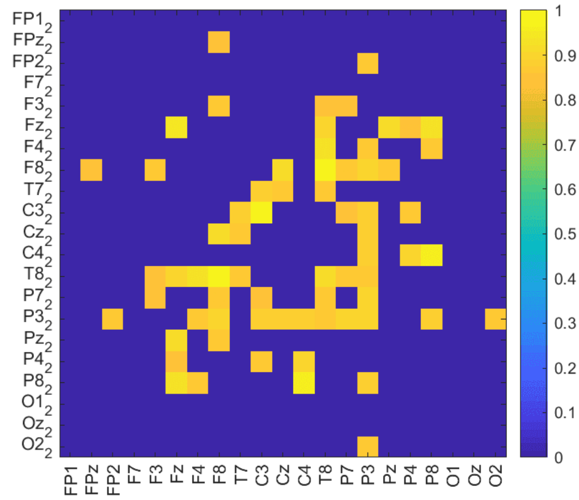
(d) Adjacency matrix of MI-based inter-brain network during cooperative interaction

Figure A.2: Adjacency matrix of MI-based team brain network for cooperation/-competition. There are more intra- and inter-brain NS on cooperation as compared with competition. Intra- and inter-brain NS have similar strength: all around 1. For intra-brain NS, (a) shows brain signals at F4 and F3 are highly synchronized; (c) shows that signals at Fz is highly synchronized with Cz,C4,P7 and P4. For INS, (b) shows signals at two subjects' C3 and F3 electrodes are highly synchronized with each other (d) shows the strong INS lies between one subject's P4 and the other subject's Fz,P7 and P4;

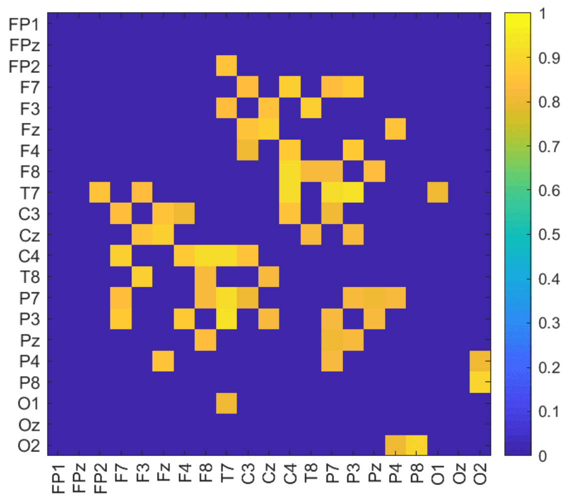
Fig.A.3 shows adjacency matrix of PLI-based intra- and inter-brain networks.



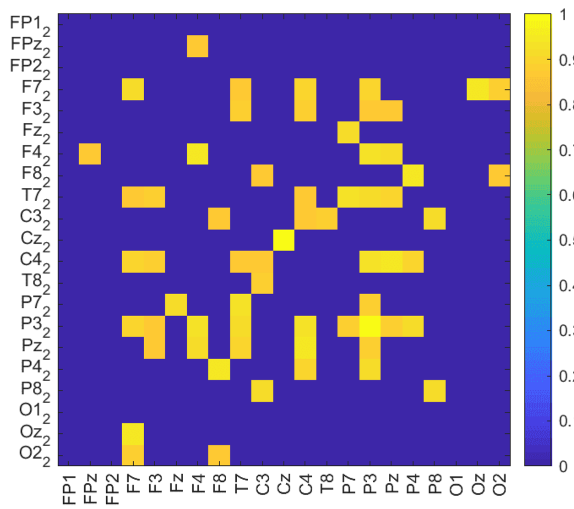
(a) The adjacency matrix of PLI-based intra-brain network during competitive interaction



(b) The adjacency matrix of PLI-based inter-brain network during competitive interaction



(c) The adjacency matrix of PLI-based intra-brain network during cooperative interaction

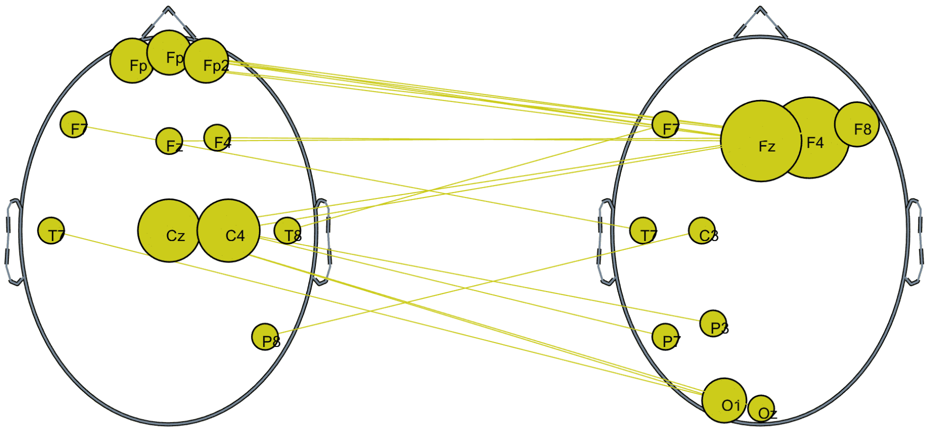


(d) The adjacency matrix of PLI-based inter-brain network during cooperative interaction

Figure A.3: Adjacency matrix of PLI-based team brain network during cooperative/-competitive interaction. There are similar amount of intra-/inter-brain NS on cooperation and competition. Intra- and inter-brain NS have similar strength during two conditions. Intra- and inter-brain NS are sparsely scattered around brain areas.

A.1.3 Statistically Significant Inter-Brain Synchrony

This subsection shows statistically significant MI-, spectral-coherence- and PLI-based INS.



[h]

Figure A.4: Statistically significant spectral-coherence-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. Cz,C4, F4 and Fz are the largest nodes

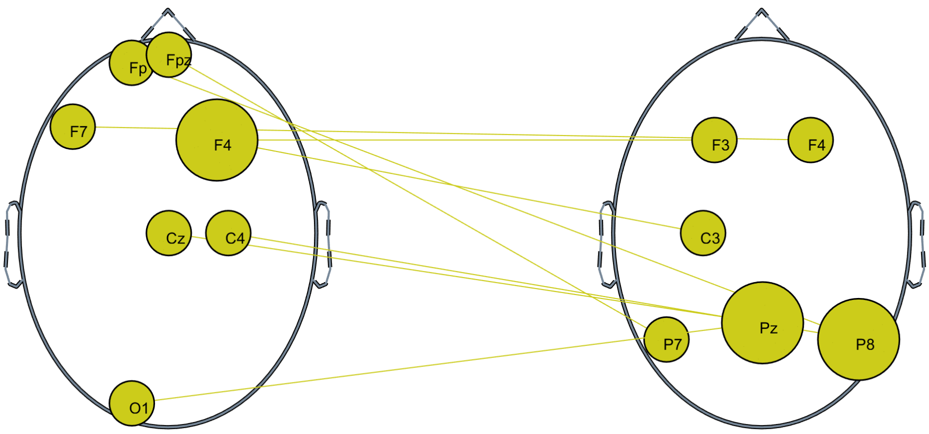


Figure A.5: Statistically significant MI-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. F4,Pz,P8 are the largest nodes

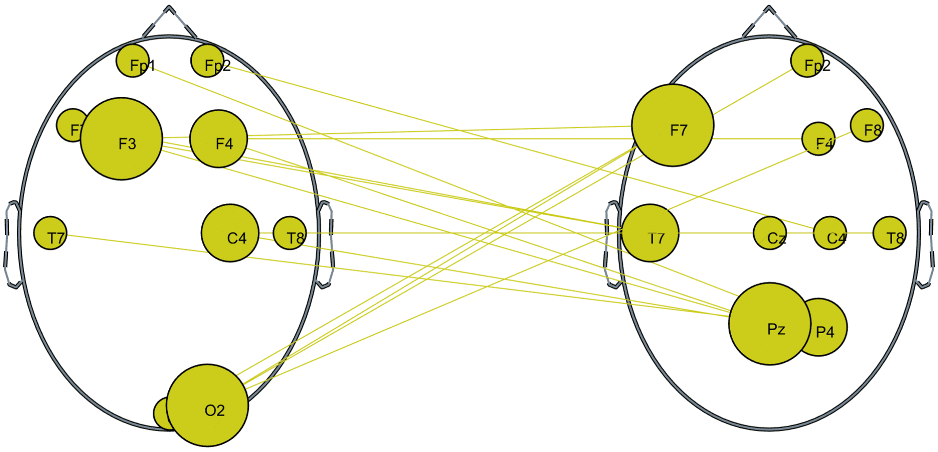


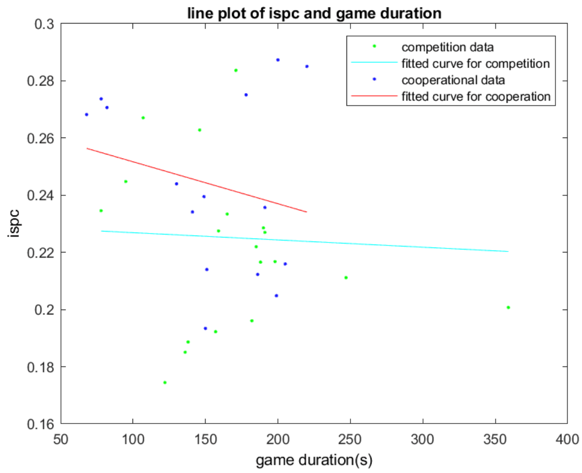
Figure A.6: Statistically significant PLI-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. F7,Pz are the largest nodes.

A.1.4 Behavioral Data

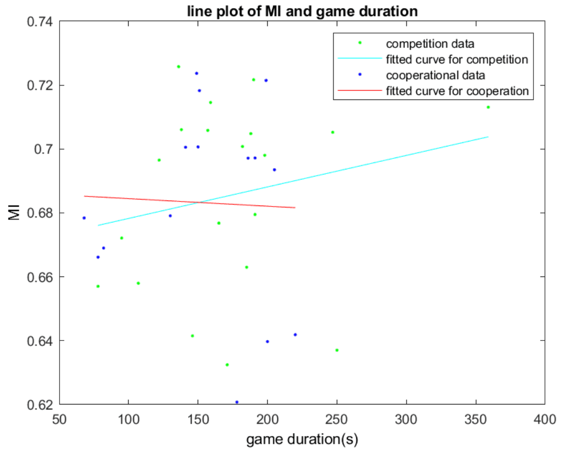
This section shows how team-performance was related with INS and GE of team-brain networks.

Team-Performance and Inter-Brain Synchrony

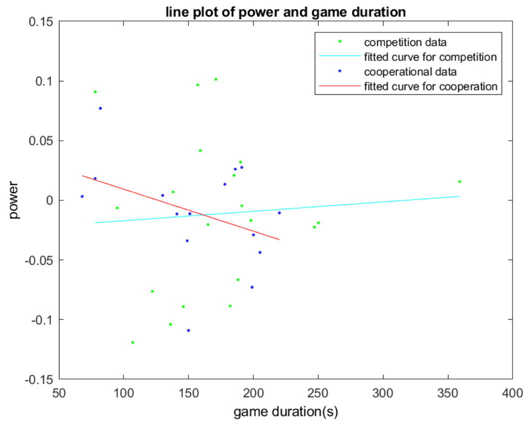
Fig.A.7a, Fig.A.7b, Fig.A.7c and Fig.A.7d show scatter plot between game duration and the ISPC-based INS, MI-based INS, power-correlation-based INS and spectral-coherence-based INS respectively.



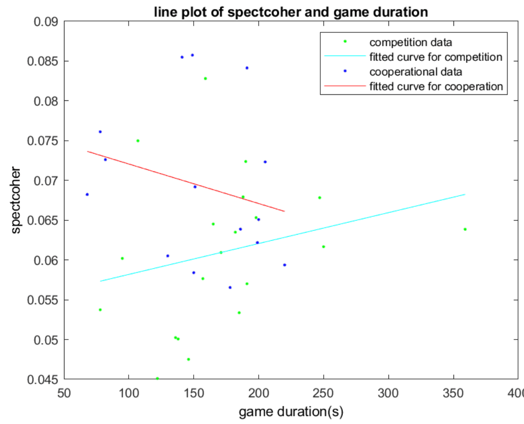
(a) Scatter-plot between game duration and ISPC-based INS



(b) Scatter-plot between game duration and MI-based INS



(c) Scatter-plot between game duration and power-correlation-based INS

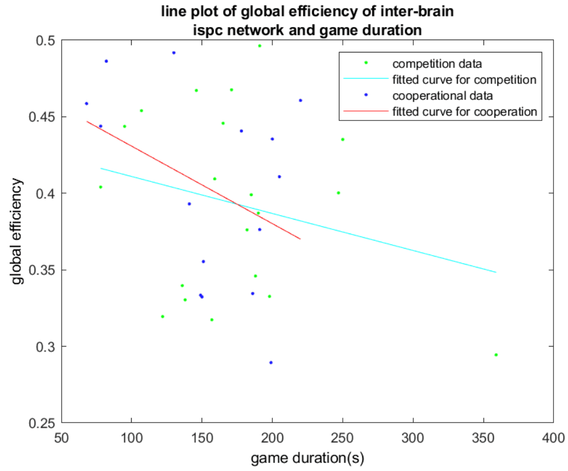


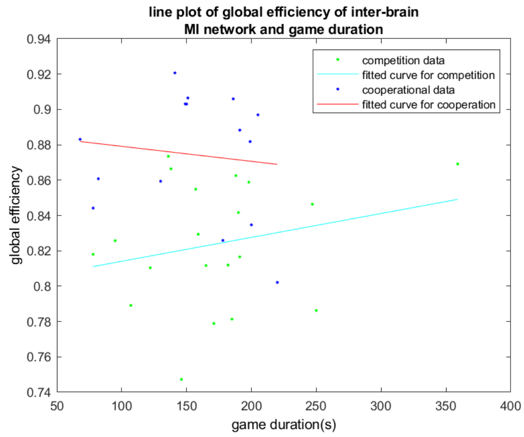
(d) Scatter-plot between game duration and spectral-coherence-based INS

Figure A.7: Scatter-plot between game-duration and the INS. Each dot is a single trial: green dots represent competitive trails while blue dots represent cooperative trials. team-performance was quantified by game duration in seconds, which are shown in x-axis. Y-axis shows INS strength. The line donates the best linear fit between predicted and original values: the blue and red lines respectively represent best fit line for the competitive and cooperative interaction. All plots show that team-performance does not associate with INS.

Team-Performance and Global Efficiency

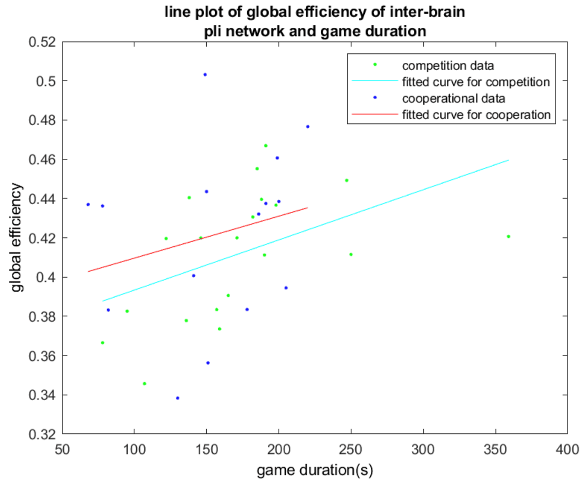
Fig.A.8a, Fig.A.8b, Fig.A.8c and Fig.A.8d show scatter plot between game duration and GE of the ISPC-based team network,the MI-based team network, the PLI-based team network and the spectral-coherence-based team brain network respectively.

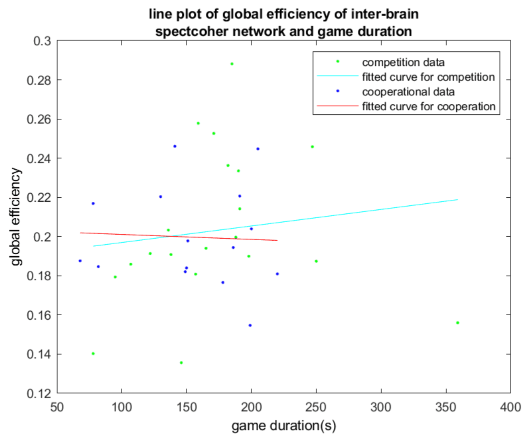




(a) Scatter-plot between game duration and the GE of ISPC-based team brain network

(b) Scatter-plot between game duration and the GE of MI-based team brain network





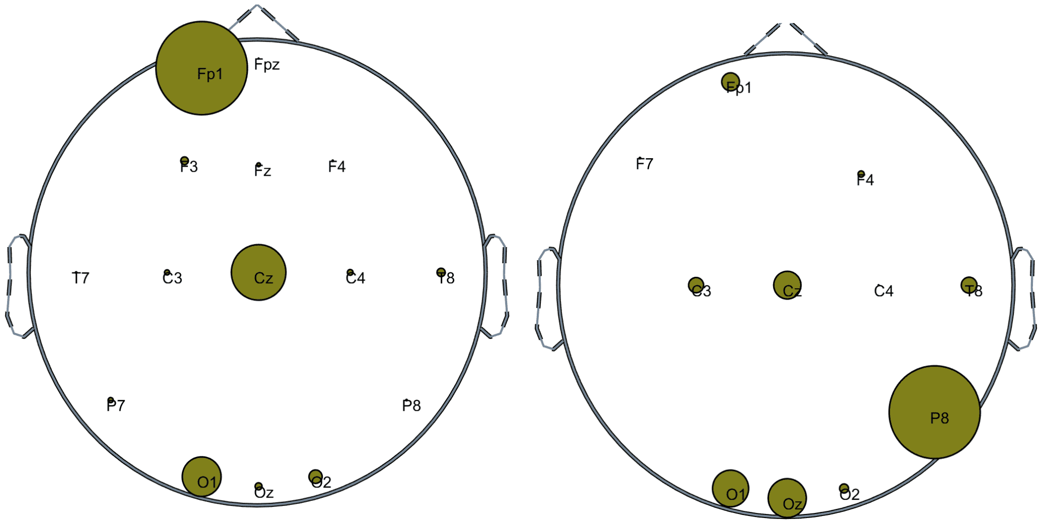
(c) Scatter-plot between game duration and the GE of PLI-based team brain network

(d) Scatter-plot between game duration and the GE of spectral-coherence-based team brain network

Figure A.8: Scatter-plot between game duration and the GE of team brain network. Each dot is a single trial: green dots represent competitive trails while blue dots represent cooperative trials. team-performance was quantified by game duration in seconds, which are shown in x-axis. Y-axis shows INS strength. The line donates the best linear fit between predicted and original values: the blue and red lines respectively represent best fit line for the competitive and cooperative interaction.

A.1.5 Brain hubs

Fig.A.9a and Fig.A.9b respectively show brain hubs of spectral-coherence-based team brain networks.



(a) Hubs of the spectral-coherence-based team brain network during competition

(b) Hubs of the spectral-coherence-based team brain network during cooperation

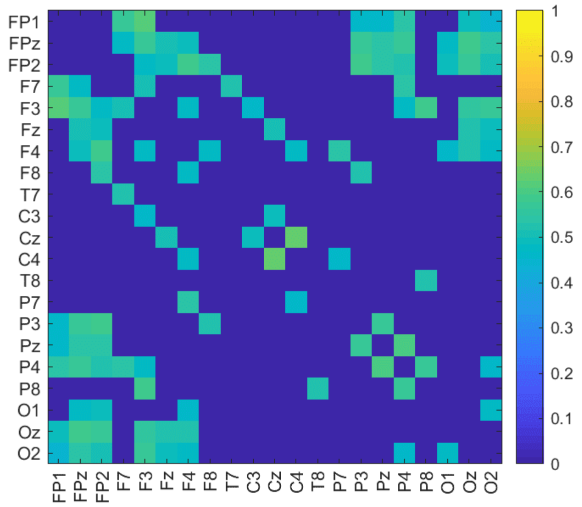
Figure A.9: Illustration of hubs of spectral-coherence-based team brain network on cooperative/competitive interaction. Hubs were measured by betweenness centrality. Fp1, Cz in (a) and P8 in (b) are most important electrodes in information exchange of the spectral-coherence-based team brain networks during competition and cooperation respectively. All plots show that team-performance does not strongly associated with GE of the team brain network.

A.2 Results Based on Last 15 Seconds of Data

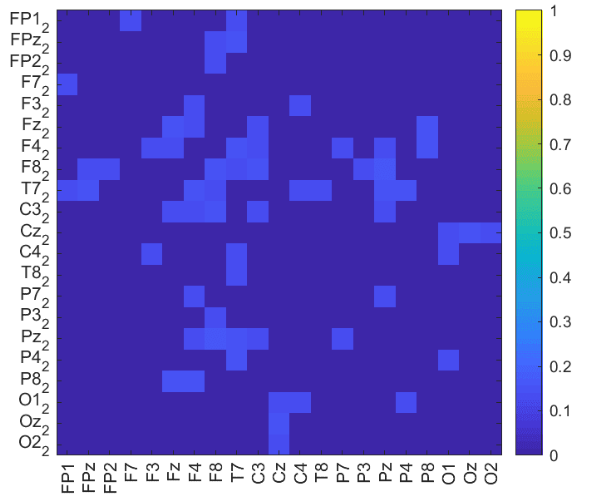
This section shows analysis results based on the last 15 seconds of the data.

A.2.1 Strong Neural Synchrony

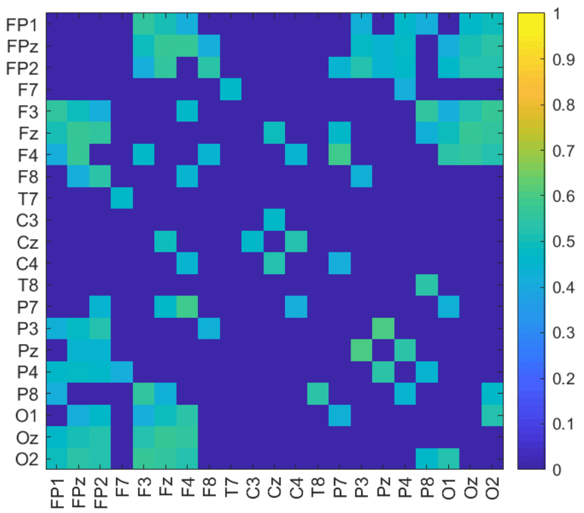
Fig.A.10,Fig.A.13, Fig.A.11 and Fig.A.12 respectively show adjacency matrix of power-correlation-, spectral-coherence-, ISPC- and PLI-based team brain networks.



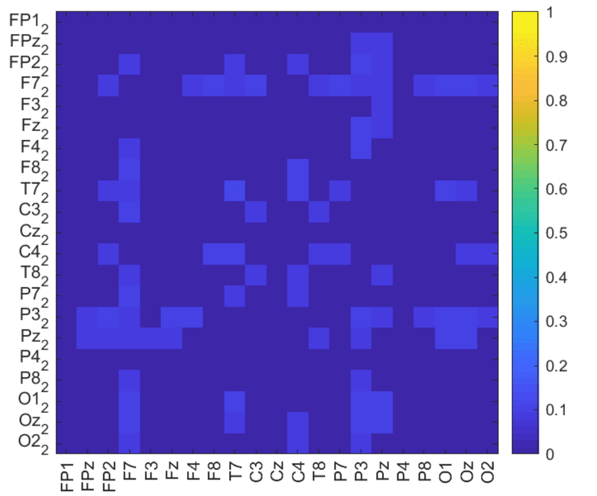
(a) Adjacency matrix of power-correlation-based intra-brain network during competitive interaction



(b) Adjacency matrix of power-correlation-based inter-brain network during competitive interaction

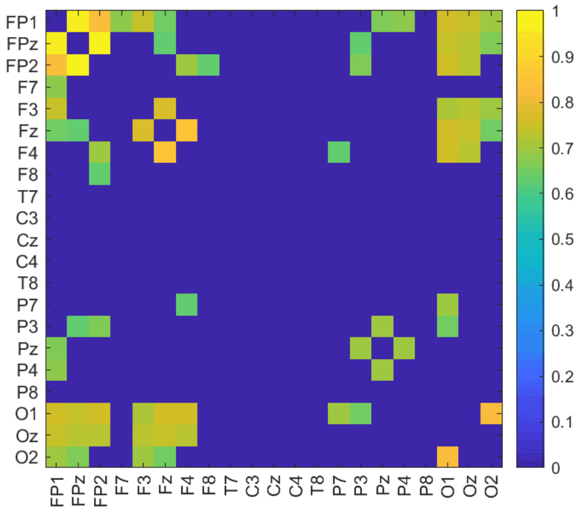


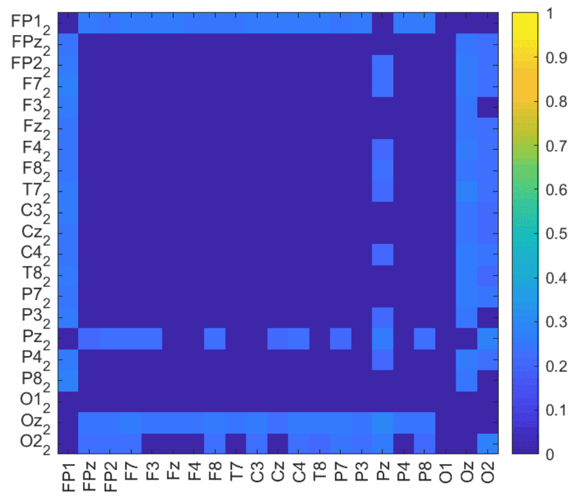
(c) Adjacency matrix of power-correlation-based intra-brain network during co-operational interaction



(d) Adjacency matrix of power-correlation-based inter-brain network during co-operational interaction

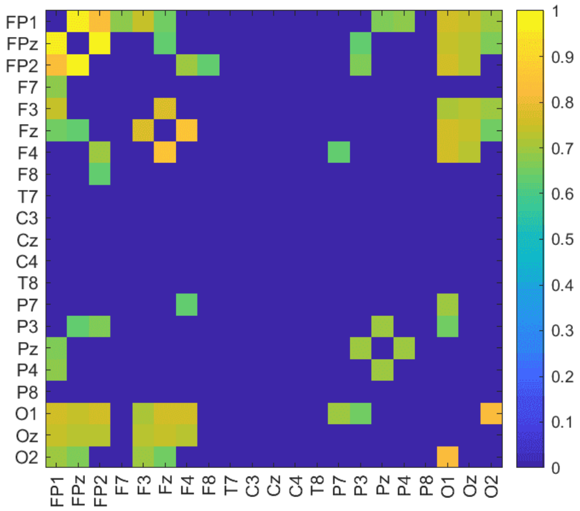
Figure A.10: Adjacency matrix of power-correlation-based team brain network.

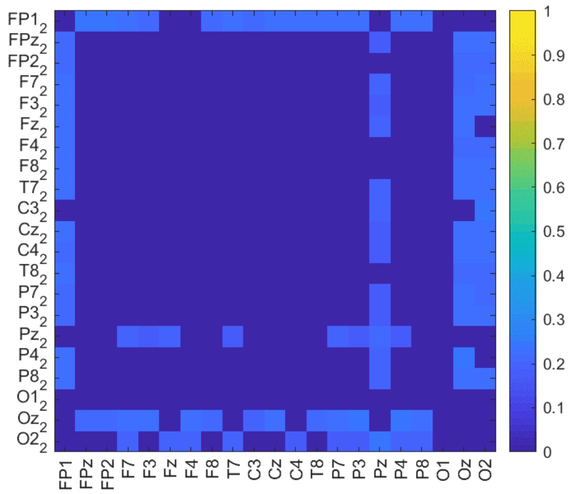




(a) Adjacency matrix of ISPC-based intra-brain network during competitive interaction

(b) Adjacency matrix of ISPC-based inter-brain network during competitive interaction

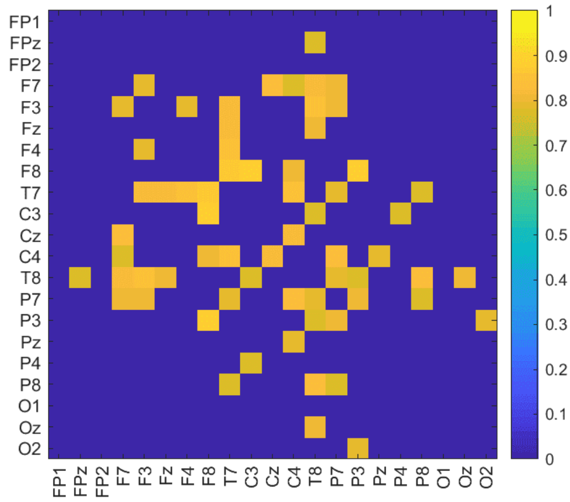




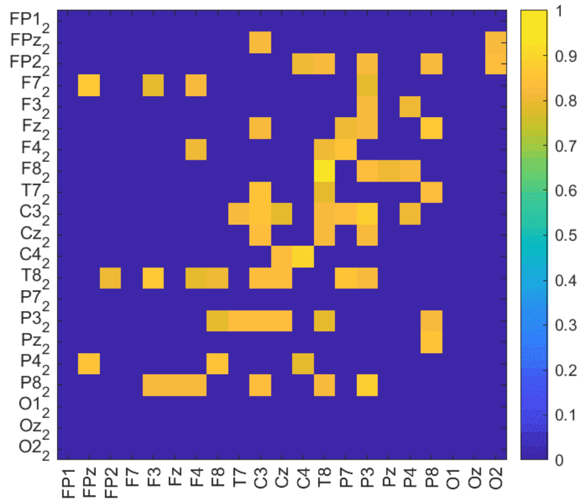
(c) Adjacency matrix of ISPC-based intra-brain network during co-operational interaction

(d) Adjacency matrix of ISPC-based inter-brain network during co-operational interaction

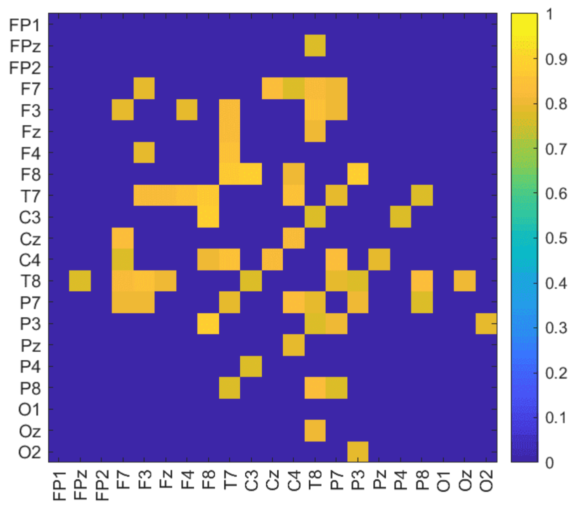
Figure A.11: Adjacency matrix of ISPC-based team brain network.



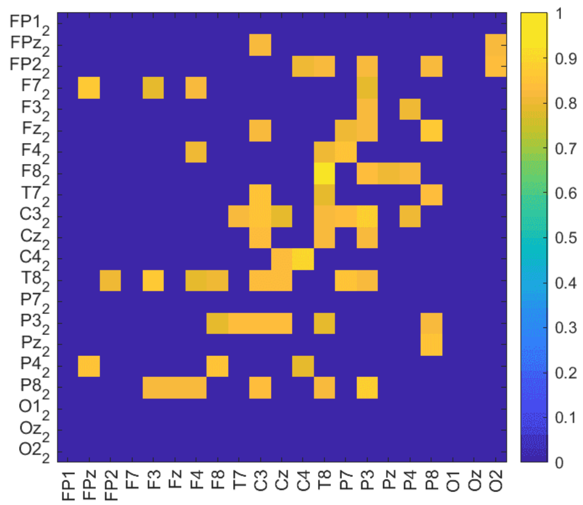
(a) Adjacency matrix of PLI-based intra-brain network during competitive interaction



(b) Adjacency matrix of PLI-based inter-brain network during competitive interaction

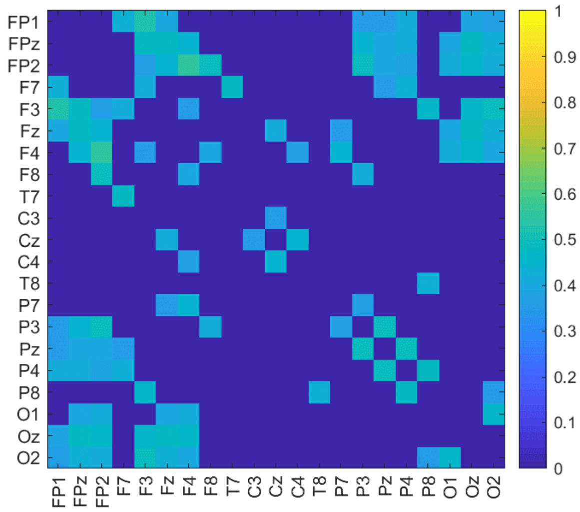


(c) Adjacency matrix of PLI-based intra-brain network during co-operational interaction

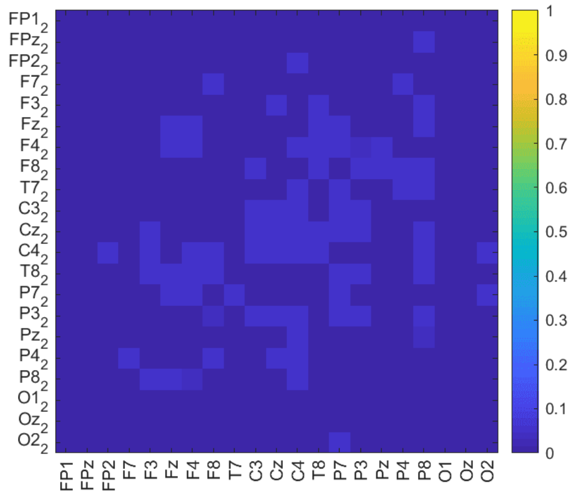


(d) Adjacency matrix of PLI-based inter-brain network during co-operational interaction

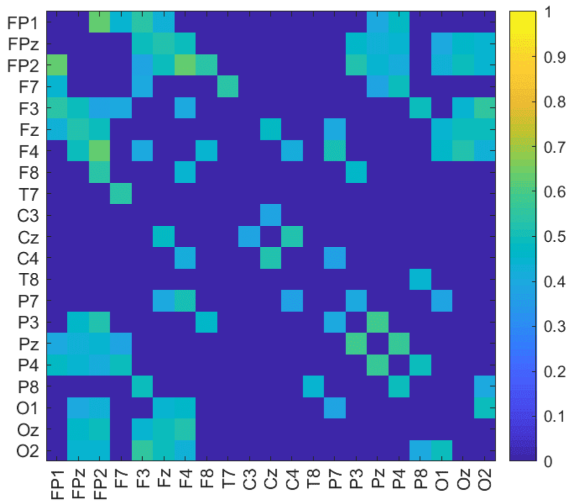
Figure A.12: Adjacency matrix of PLI-based team brain network.



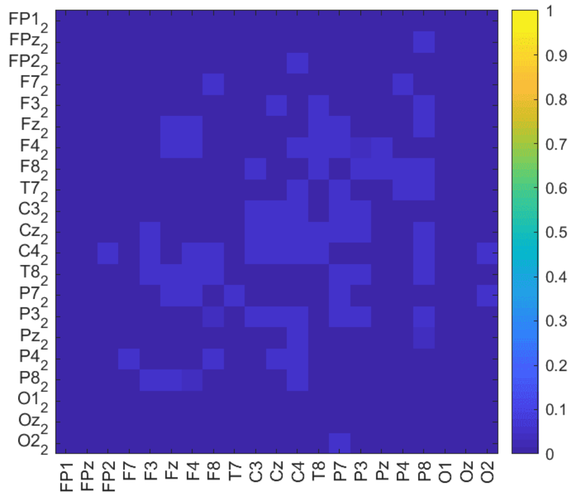
(a) Adjacency matrix of spectral-coherence-based intra-brain network during competitive interaction



(b) Adjacency matrix of spectral-coherence-based inter-brain network during competitive interaction



(c) Adjacency matrix of spectral-coherence-based intra-brain network during co-operational interaction



(d) Adjacency matrix of spectral-coherence-based inter-brain network during co-operational interaction

Figure A.13: Adjacency matrix of spectral-coherence-based team brain network.

A.2.2 Statistically Significant Inter-Brain Synchrony

Fig.A.14 and Fig.A.15 respectively illustrates PLI- and power-correlation-based statistically significant INS between cooperation and competition.

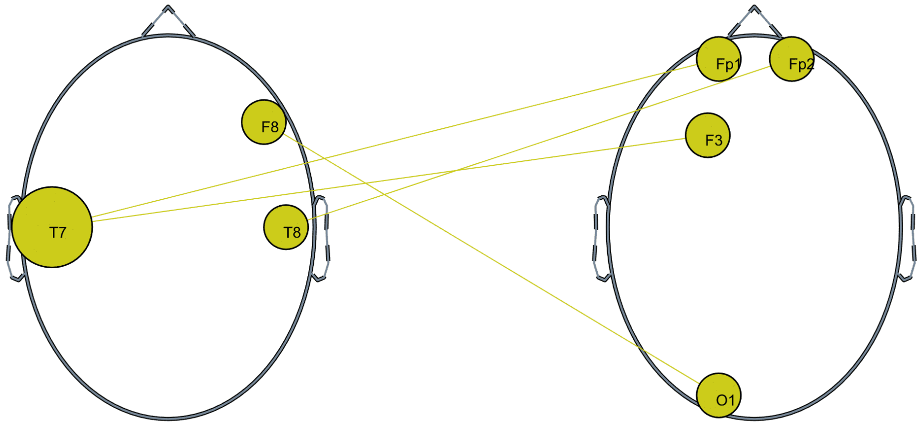


Figure A.14: Statistically significant PLI-based INS are illustrated for cooperation vs. competition.Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large.

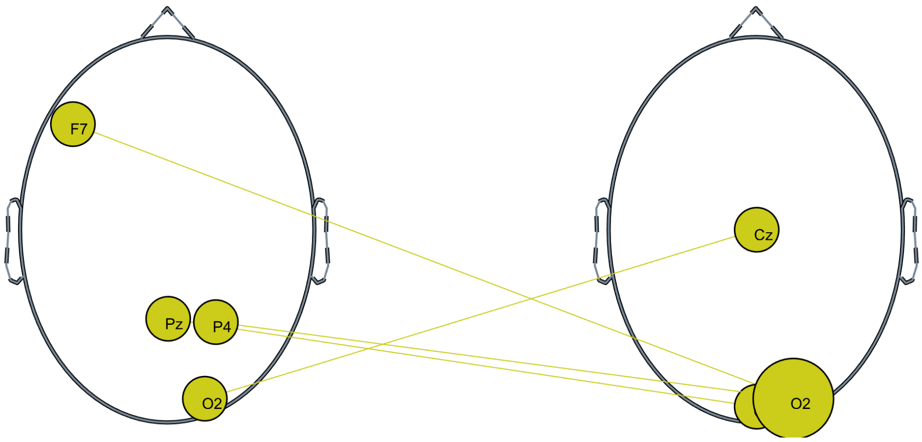


Figure A.15: Statistically significant power-correlation-based INS are illustrated for cooperation vs. competition.Lines represent statistically significant INSs. Node represent electrode. Node has more links are larger.

Fig.A.16,Fig.A.17 respectively illustrates ispc- and spectral-coherence-based statistically significant INS between cooperation and competition.

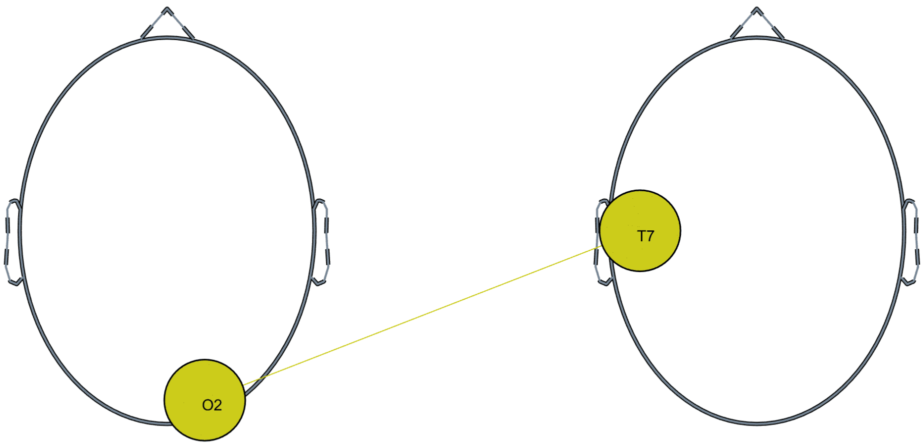


Figure A.16: Statistically significant ISPC-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are larger.

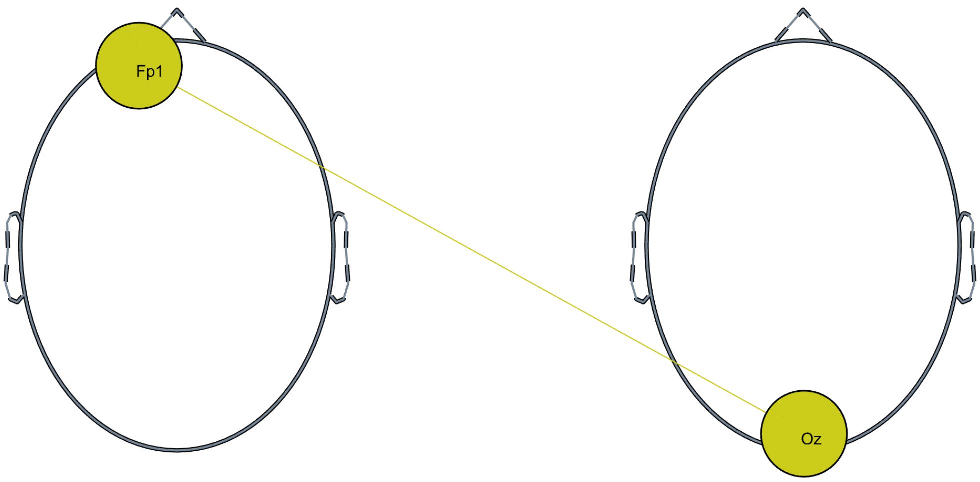


Figure A.17: Statistically significant spectral-coherence-based INS are illustrated for cooperation vs. competition.Lines represent statistically significant INSs. Node represent electrode. Node has more links are larger.

Fig.A.18 illustrates statistically significant MI-based INS between cooperation and competition. Notably, results based on 1-second-epoched data show that there is no statistically significant PLI- and MI-based INS.

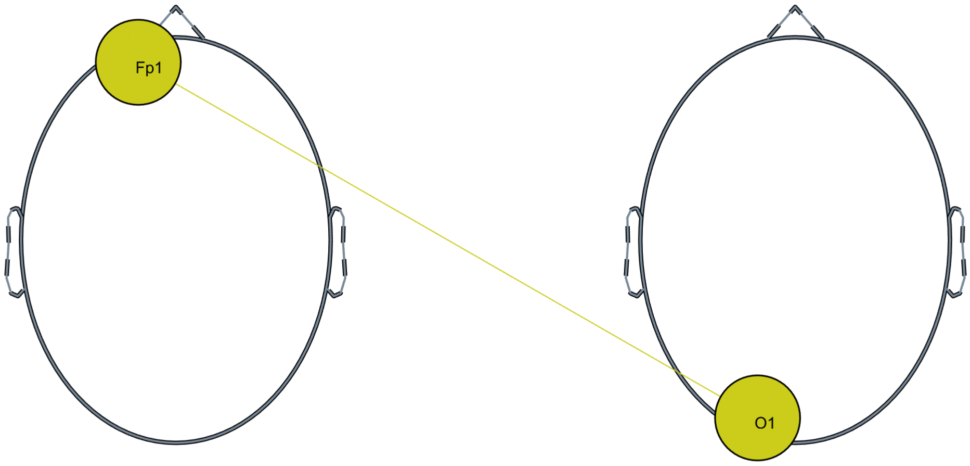
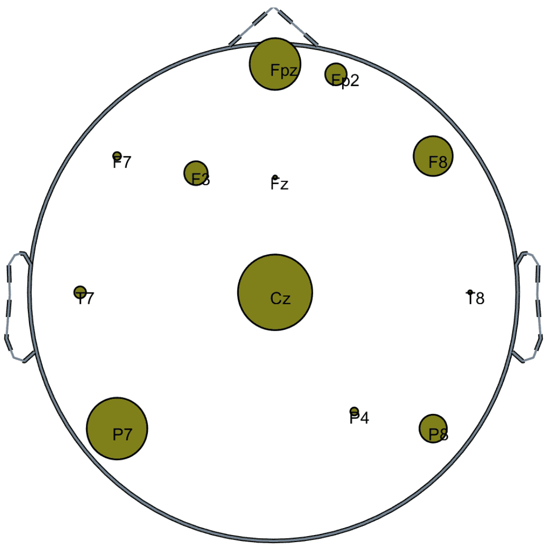


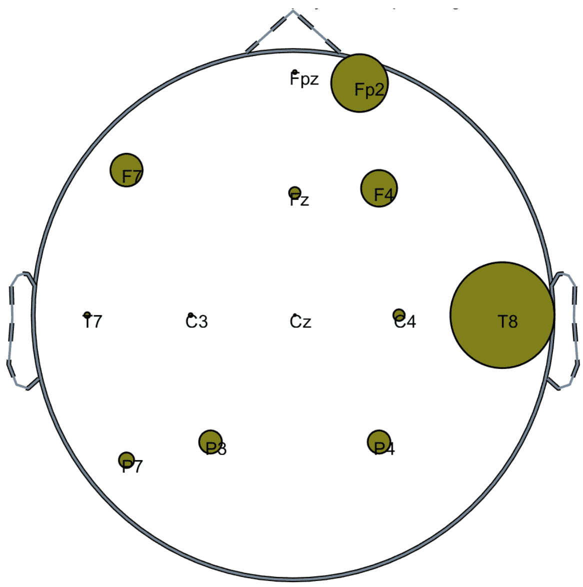
Figure A.18: Statistically significant MI-based INS are illustrated for cooperation vs. competition.Lines represent statistically significant INSs. Node represent electrode. Node has more links are larger.

A.2.3 Brain Hubs

Fig.A.19a and Fig.A.19b illustrate the hubs for ISPC-based team brain network during competition and cooperation respectively.

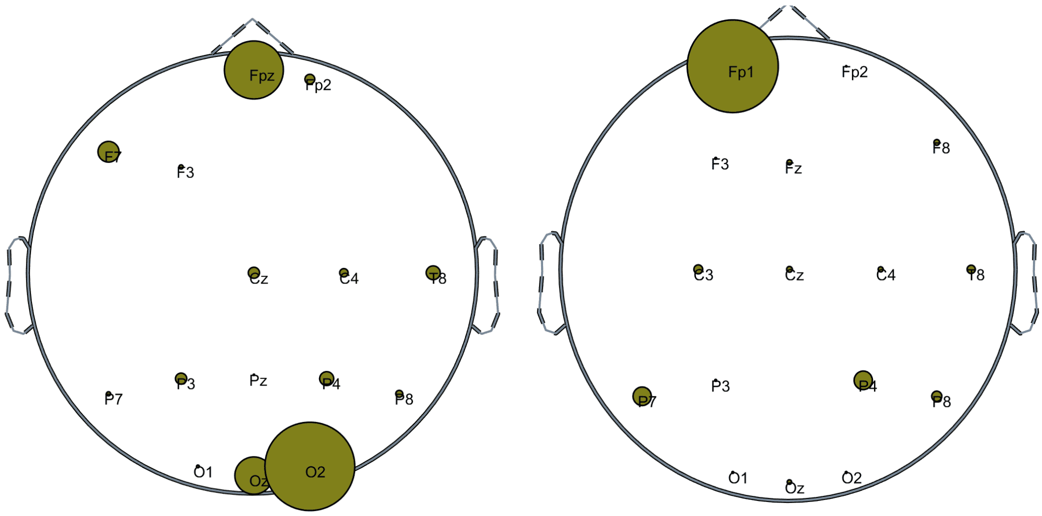


(a) Hubs of the ISPC-based team brain network during competition



(b) Hubs of the ISPC-based team brain network during cooperation

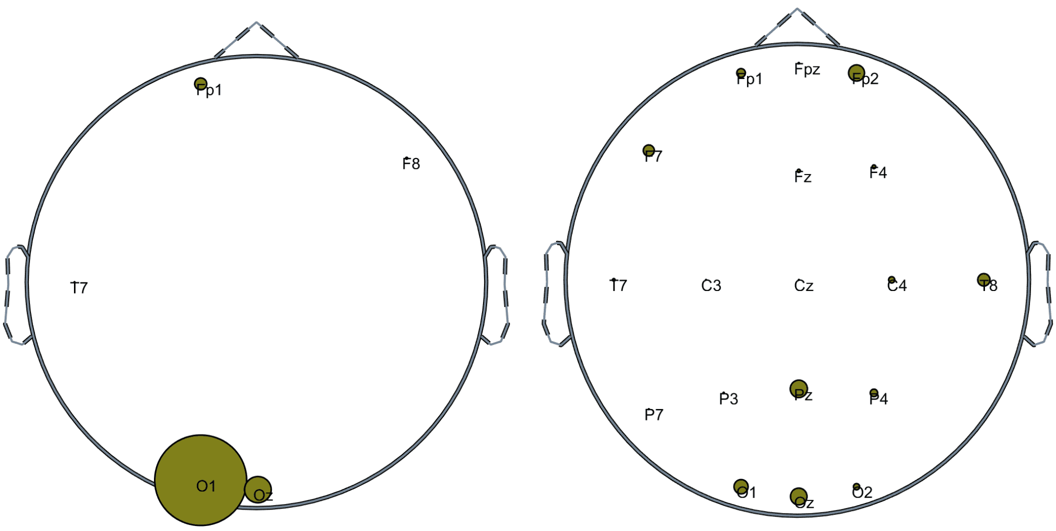
Figure A.19: Illustration of hubs of ISPC-based team brain network on cooperative/competitive interaction. Hubs were measured by betweenness centrality.



(a) Hubs of the power-correlation-based team brain network during competition

(b) Hubs of the power-correlation-based team brain network during cooperation

Figure A.20: Illustration of hubs of power-correlation-based team brain network on cooperative/competitive interaction. Hubs were measured by betweenness centrality.



(a) Hubs of the spectral-coherence-based team brain network during competition

(b) Hubs of the spectral-coherence-based team brain network during cooperation

Figure A.21: Illustration of hubs of spectral-coherence-based team brain network on cooperative/competitive interaction. Hubs were measured by betweenness centrality.

Fig.A.20a and Fig.A.20b illustrate the hubs for power-correlation-based team brain network during competition and cooperation respectively. Fig.A.21a and Fig.A.21b illustrate the hubs for spectral-coherence-based team brain network during competition and cooperation respectively. Consistent with previous findings, there is no brain hubs for MI and PLI-based team brain networks.

A.2.4 Topological Properties

Global Efficiency

Tab.A.1 shows GE for team- and intra-brain networks. These results are consistent with previous findings.(Sec.A.3.4).

	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.3642	0.3442	0.4880	0.4688
Power-correlation	0.2445	0.2115	0.5343	0.3177
Spectral-coherence	0.1673	0.1717	0.6798	0.3184

Table A.1: GE of team- and intra-brain networks

Small-World-Ness

Tab.A.2 shows the SWN of the team- and intra- brain networks.

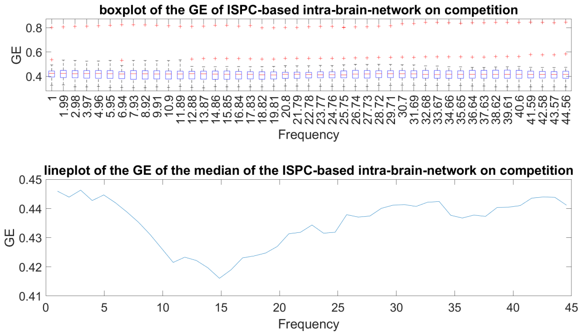
	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.9446	0.9923	0.9380	0.9458
Power-correlation	1.1550	1.4169	0.9161	1.1066
Spectral-coherence	1.6940	1.9148	0.9000	1.1445

Table A.2: SWN of the team- and intra-brain networks

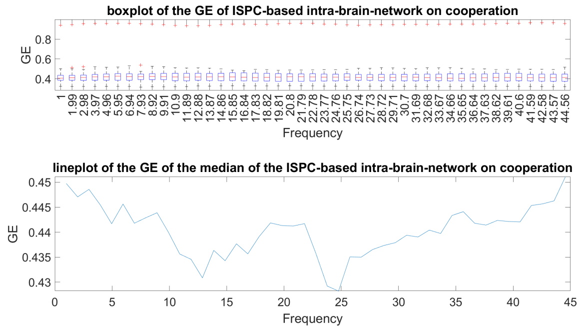
A.2.5 Global Efficiency and Small-World-ness over time/frequency

GE over time/frequency

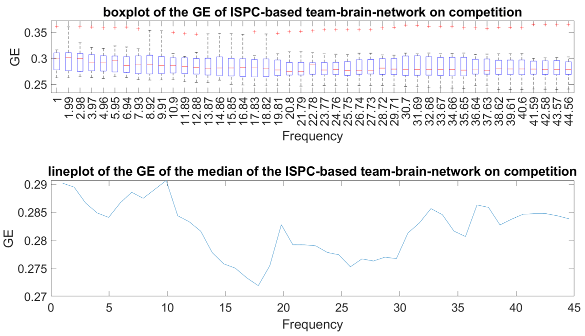
This section show GE of ISPC- and power-correlation-based network over time and frequency.



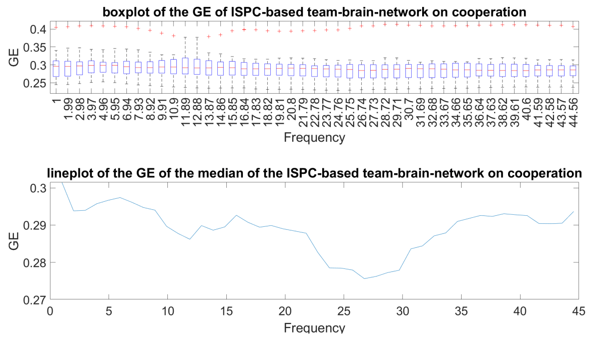
(a) GE of competitive ISPC-based intra-brain network over frequency



(b) GE of cooperative ISPC-based intra-brain network over frequency

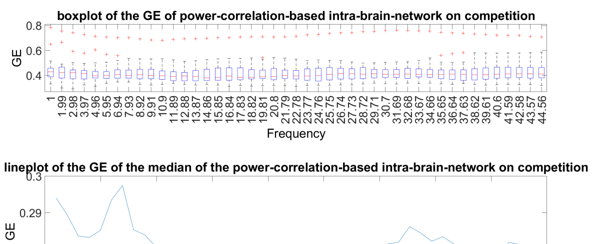


(c) GE of competitive ISPC-based team-brain network over frequency

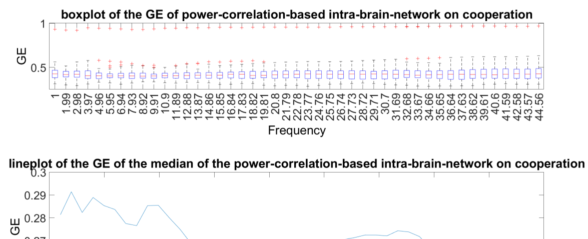


(d) GE of cooperative ISPC-based team-brain network over frequency

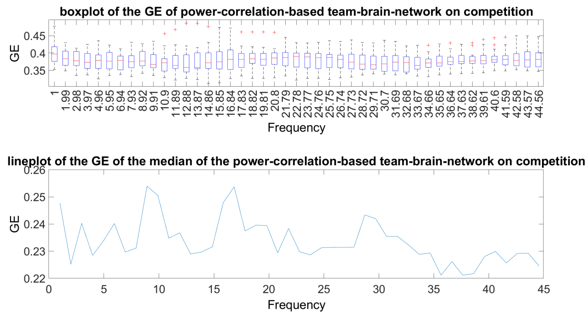
Figure A.22: GE of ISPC-based intra- and team-brain network over frequency. In (a),(b),(c),(d), the upper boxplot shows how GE of the network changes over frequency; the lower line-plot shows how GE of the network of median ISPC changes over frequency.



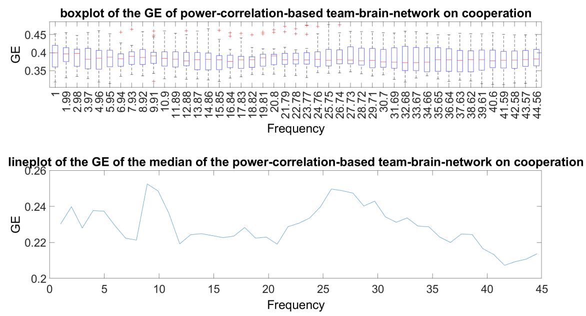
(a) GE of competitive power-correlation-based intra-brain network over frequency



(b) GE of cooperative power-correlation-based intra-brain network over frequency

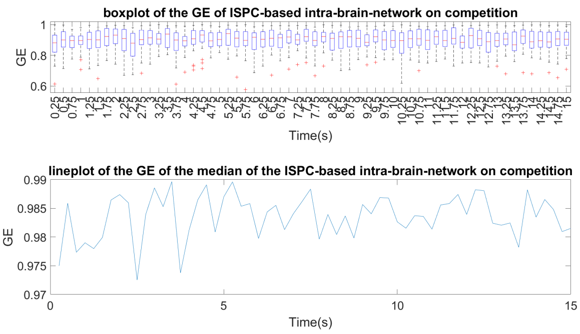


(c) GE of competitive power-correlation-based team-brain network over frequency

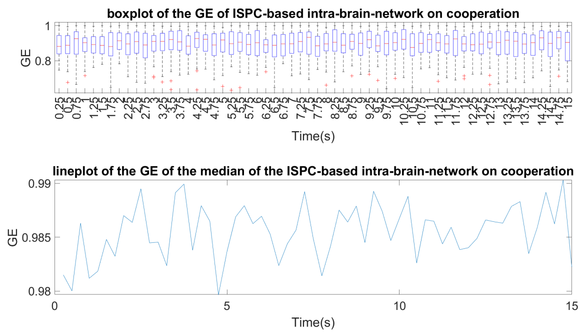


(d) GE of cooperative power-correlation-based team-brain network over frequency

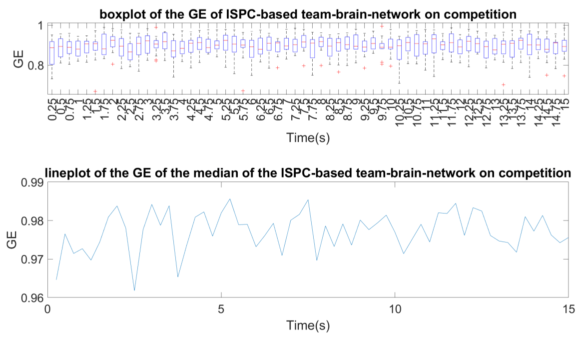
Figure A.22: GE of power-correlation-based intra- and team-brain network over frequency. In (a),(b),(c),(d), the upper boxplot shows how GE of the network changes over frequency; the lower line-plot shows how GE of the network of median power-correlation changes over frequency.



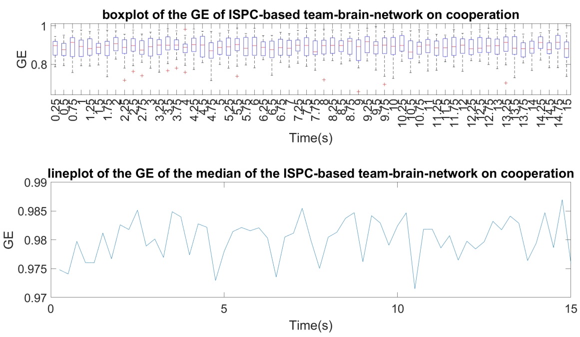
(a) GE of competitive ISPC-based intra-brain network over time



(b) GE of cooperative ISPC-based intra-brain network over time

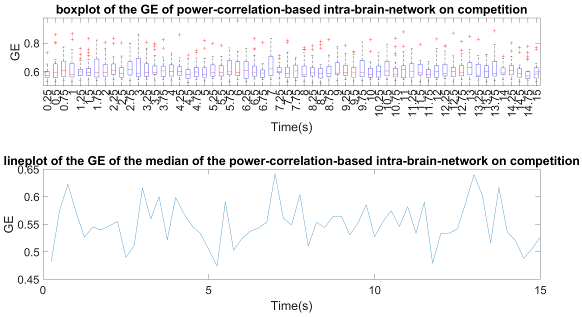


(c) GE of competitive ISPC-based team-brain network over time

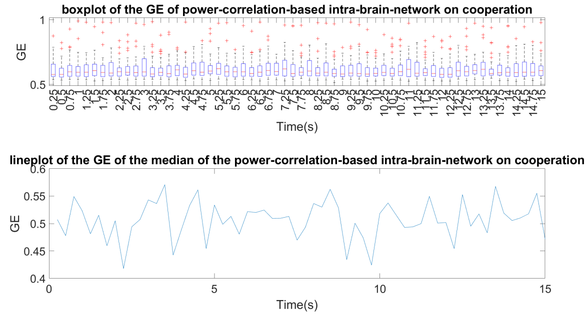


(d) GE of cooperative ISPC-based team-brain network over time

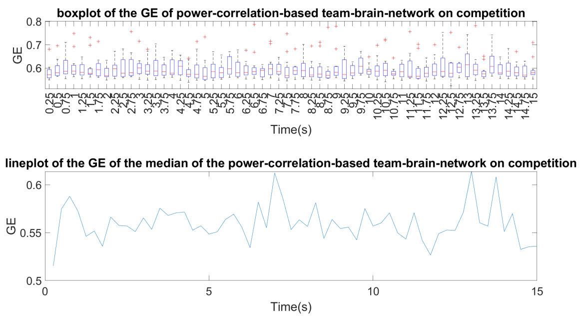
Figure A.23: GE of ISPC-based intra- and team-brain network over time. In (a),(b),(c),(d), the upper boxplot shows how GE of the network changes over time; the lower line-plot shows how GE of the network of median ISPC changes over time.



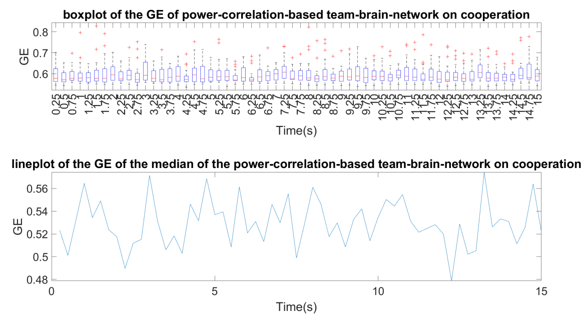
(a) GE of competitive power-correlation-based intra-brain network over time



(b) GE of cooperative power-correlation-based intra-brain network over time



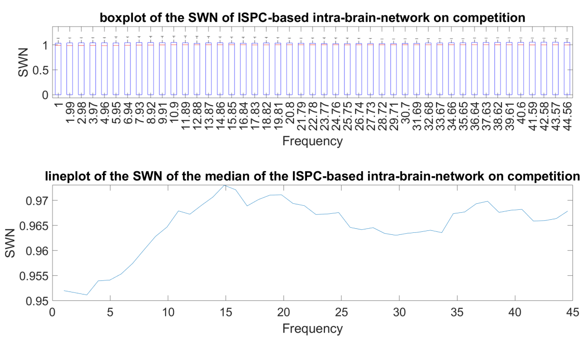
(c) GE of competitive power-correlation-based team-brain network over time



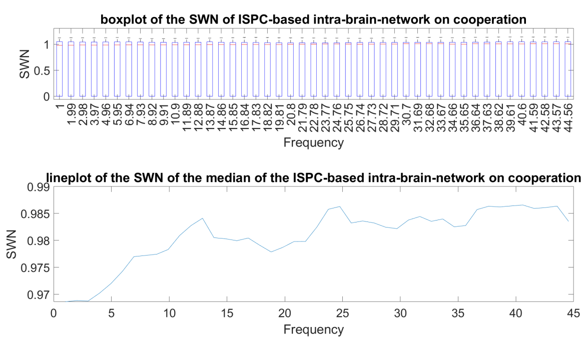
(d) GE of cooperative power-correlation-based team-brain network over time

Figure A.24: GE of power-correlation-based intra- and team-brain network over time.In (a),(b),(c),(d), the upper boxplot shows how GE of the network changes over time; the lower line-plot shows how GE of the network of median power-correlation changes over time.

Small-world-ness over time/frequency

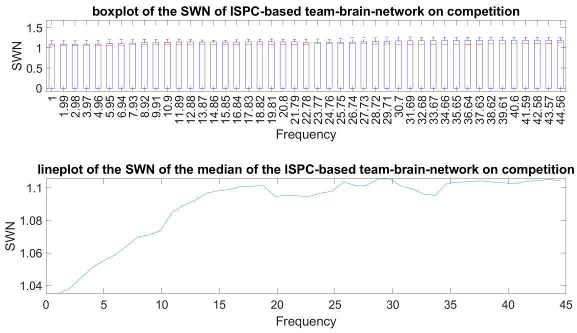


(a) SWN of competitive ISPC-based intra-bain network over frequency

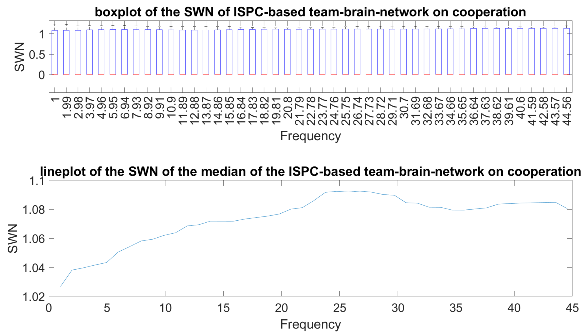


(b) SWN of cooperative ISPC-based intra-brain network over frequency

Figure A.25: SWN of ISPC-based intra- and team-brain network over frequency.

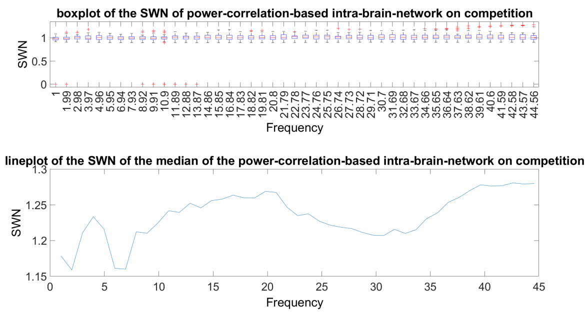


(c) SWN of competitive ISPC-based team-brain network over frequency

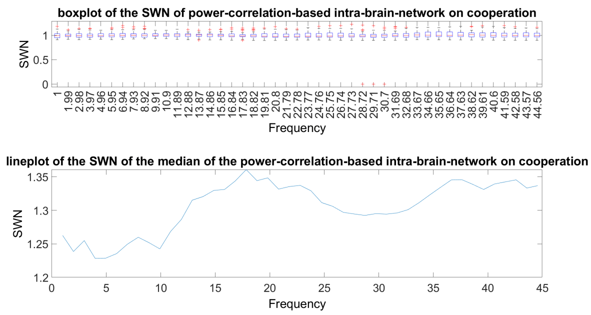


(d) SWN of cooperative ISPC-based team-brain network over frequency

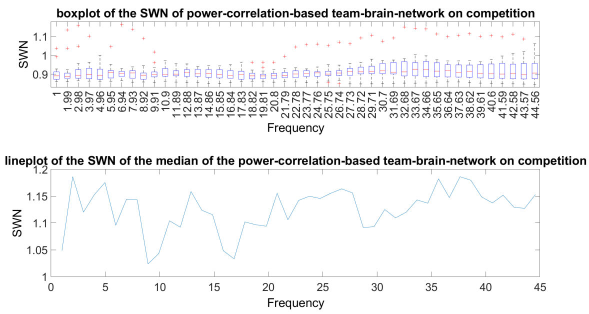
Figure A.25: SWN of ISPC-based intra- and team-brain network over frequency(Cont). In (a),(b),(c),(d), the upper boxplot shows how SWN of the network changes over frequency; the lower line-plot shows how SWN of the network of median ISPC changes over frequency.



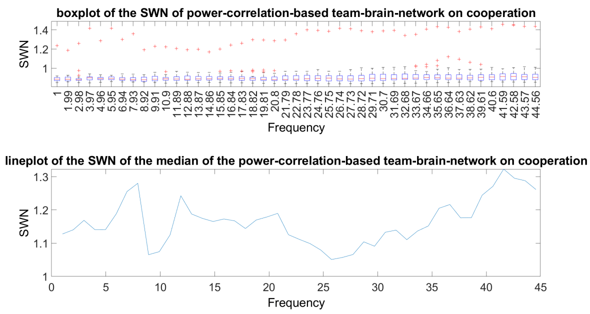
(a) SWN of competitive power-correlation-based intra-brain network over frequency



(b) SWN of cooperative power-correlation-based intra-brain network over frequency

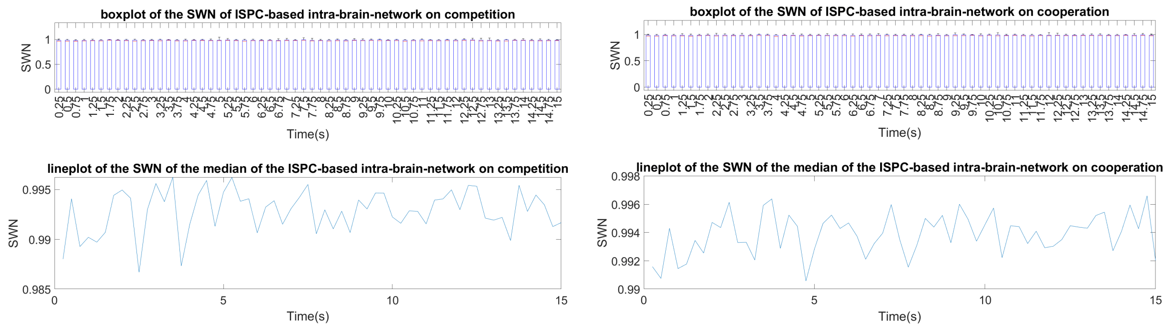


(c) SWN of competitive power-correlation-based team-brain network over frequency



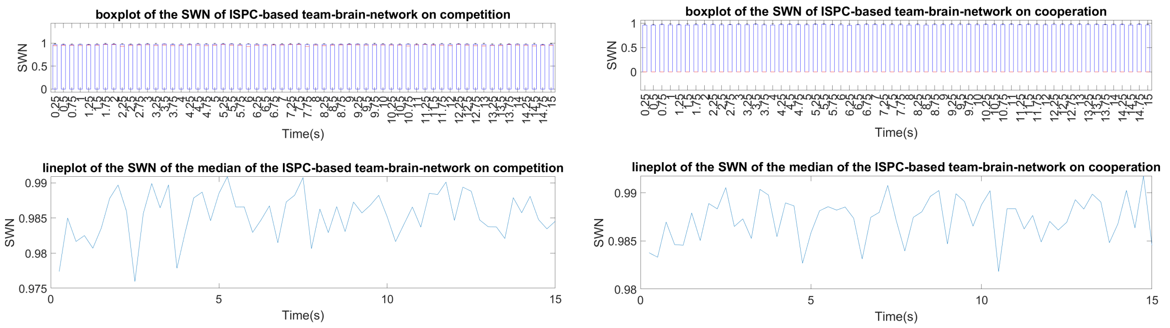
(d) SWN of cooperative power-correlation-based team-brain network over frequency

Figure A.26: SWN of power-correlation-based intra- and team-brain network over frequency. In (a),(b),(c),(d), the upper boxplot shows how SWN of the network changes over frequency; the lower line-plot shows how SWN of the network of median power-correlation changes over frequency.



(a) SWN of competitive ISPC-based intra-brain network over time

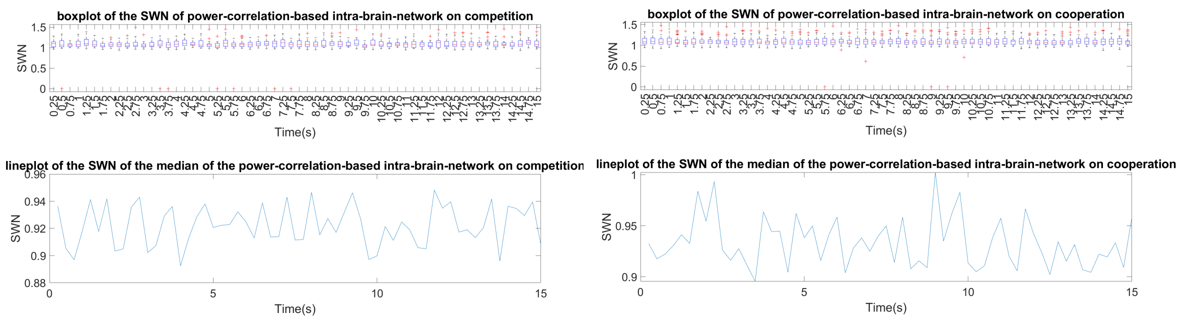
(b) SWN of cooperative ISPC-based intra-brain network over time



(c) SWN of competitive ISPC-based team-brain network over time

(d) SWN of cooperative ISPC-based team-brain network over time

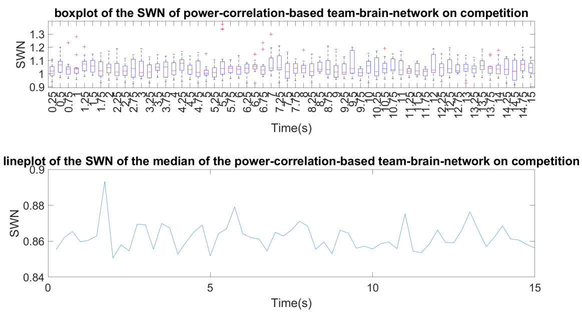
Figure A.27: SWN of ISPC-based intra- and team-brain network over time. In (a),(b),(c),(d), the upper box-plot shows how SWN of the network changes over time; the lower line-plot shows how GE of the network of median ISPC changes over time.



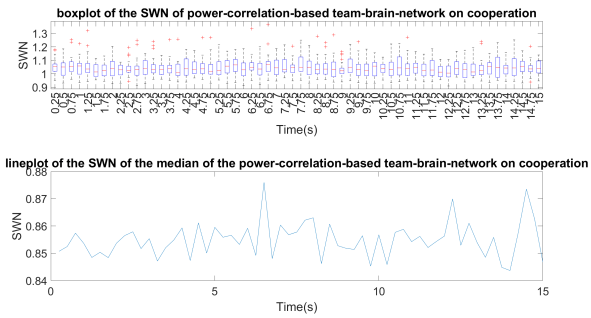
(a) SWN of competitive power-correlation-based intra-brain network over time

(b) SWN of cooperative power-correlation-based intra-brain network over time

Figure A.28: SWN of power-correlation-based intra- and team-brain network over time.



(c) SWN of competitive power-correlation-based team-brain network over time



(d) SWN of cooperative power-correlation-based team-brain network over time

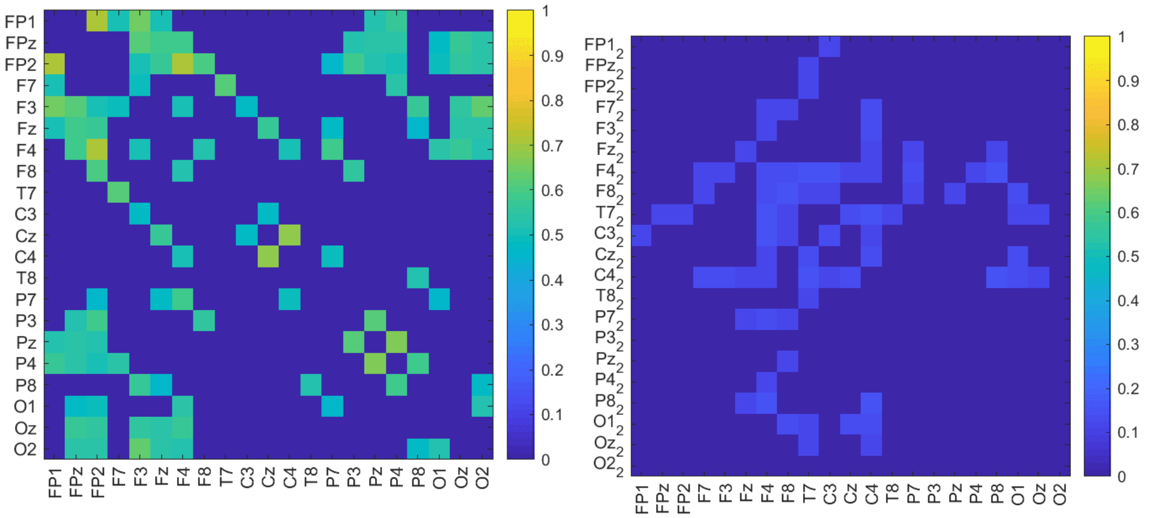
Figure A.28: SWN of power-correlation-based intra- and team-brain network over time (Cont.). In (a),(b),(c),(d), the upper box-plot shows how SWN of the network changes over time; the lower line-plot shows how SWN of the network of median power-correlation changes over time.

A.3 Results Based on Last 30 seconds of Data

This section shows analysis results from the data based on the last 30 seconds of brain signals.

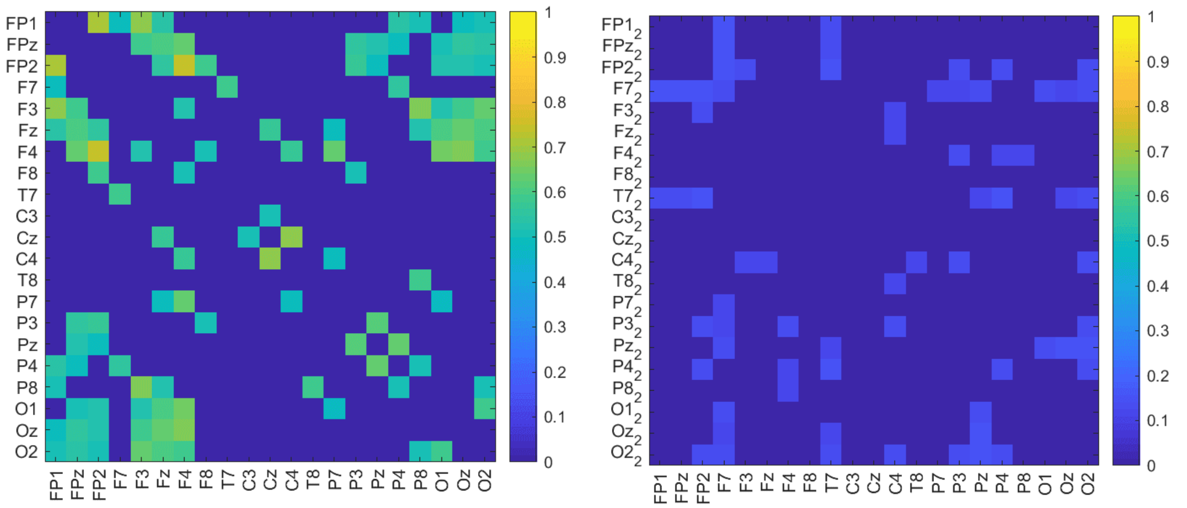
A.3.1 Strong Neural Synchrony

Fig.A.29,Fig.A.30, Fig.A.31 and Fig.A.32 respectively show adjacency matrix of power-correlation-, ISPC-, PLI- and spectral-coherence-based brain networks. Notably, threshold was one standard deviation plus median of intra- and inter-brain NS without outliers.



(a) Adjacency matrix of power-correlation-based intra-brain network during competitive interaction

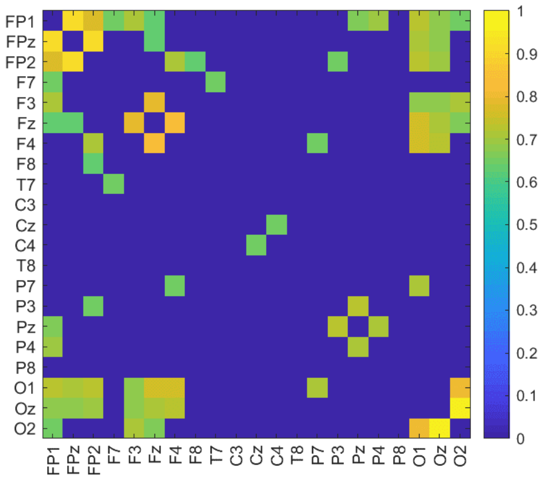
(b) Adjacency matrix of power-correlation-based inter-brain network during competitive interaction



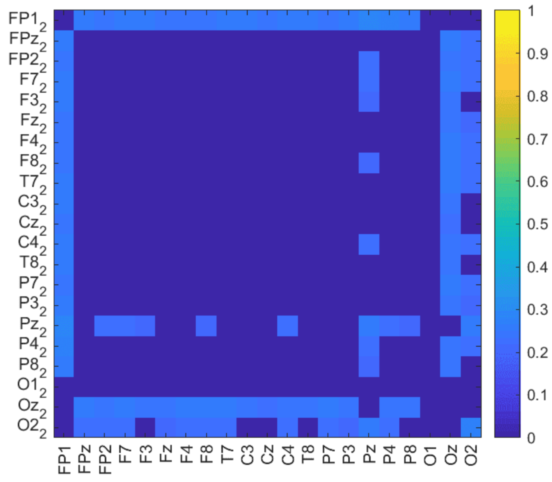
(c) Adjacency matrix of power-correlation-based intra-brain network during co-operational interaction

(d) Adjacency matrix of power-correlation-based inter-brain network during co-operational interaction

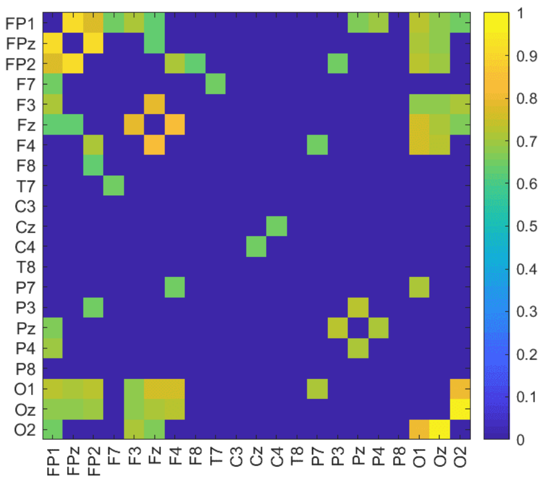
Figure A.29: Adjacency matrix of power-correlation-based team brain network.



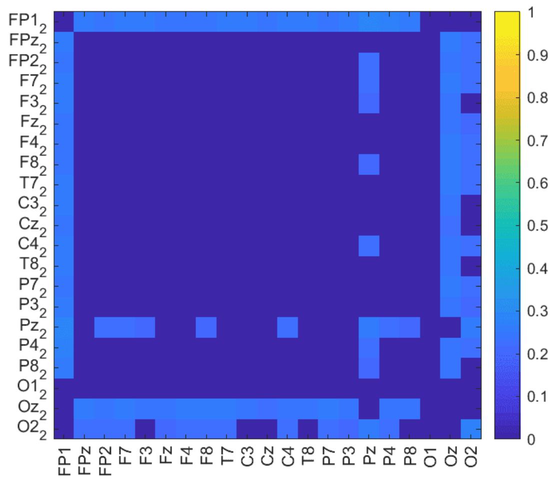
(a) Adjacency matrix of ISPC-based intra-brain network during competitive interaction



(b) Adjacency matrix of ISPC-based inter-brain network during competitive interaction

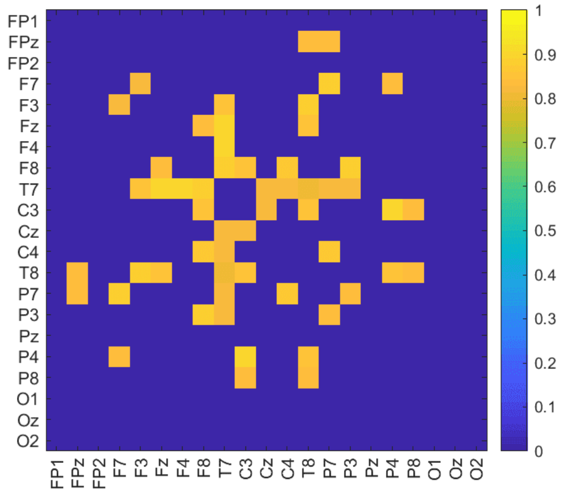


(c) Adjacency matrix of ISPC-based intra-brain network during co-operational interaction

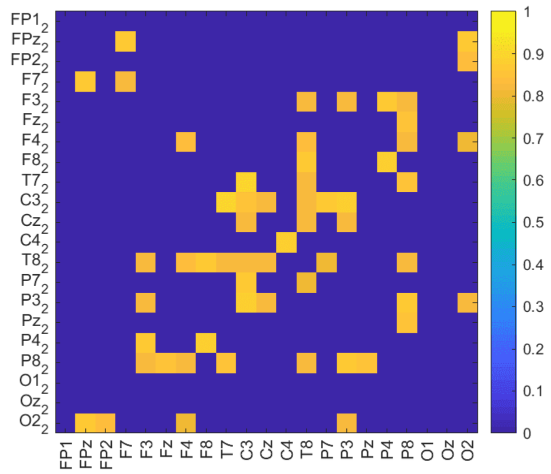


(d) Adjacency matrix of ISPC-based inter-brain network during co-operational interaction

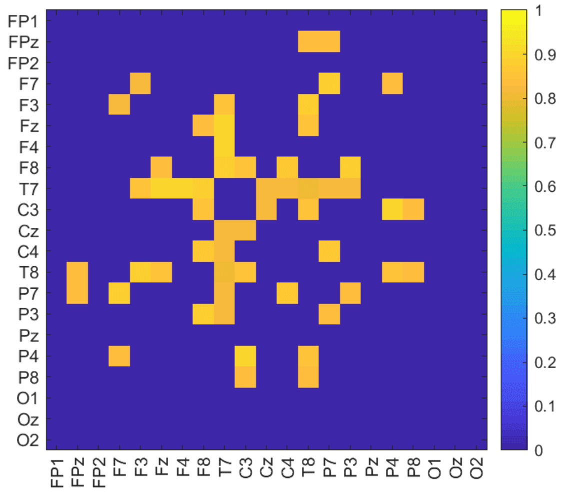
Figure A.30: Adjacency matrix of ISPC-based team brain network.



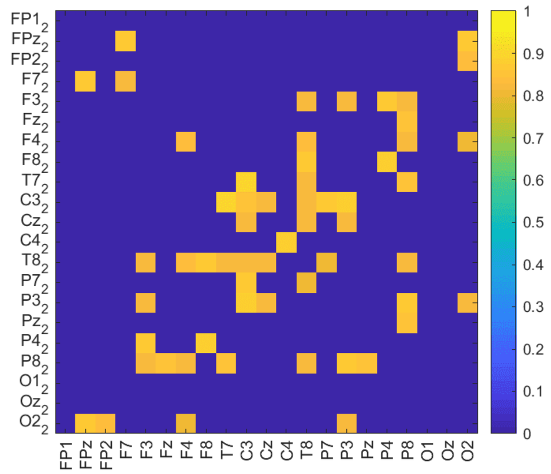
(a) Adjacency matrix of PLI-based intra-brain network during competitive interaction



(b) Adjacency matrix of PLI-based inter-brain network during competitive interaction

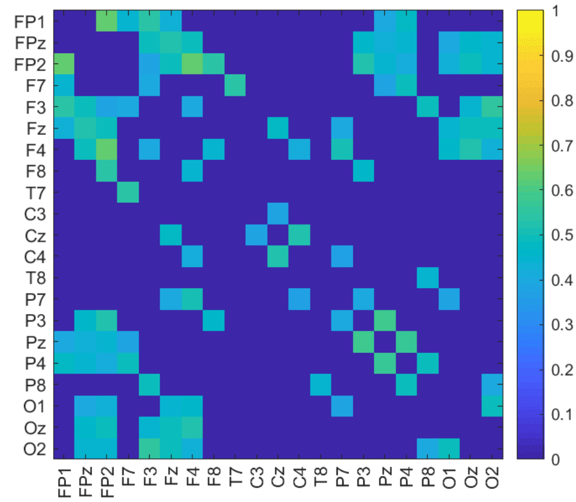


(c) Adjacency matrix of PLI-based intra-brain network during co-operational interaction

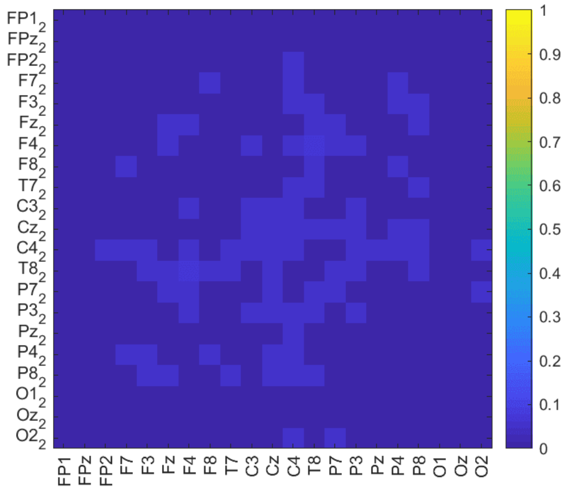


(d) Adjacency matrix of PLI-based inter-brain network during co-operational interaction

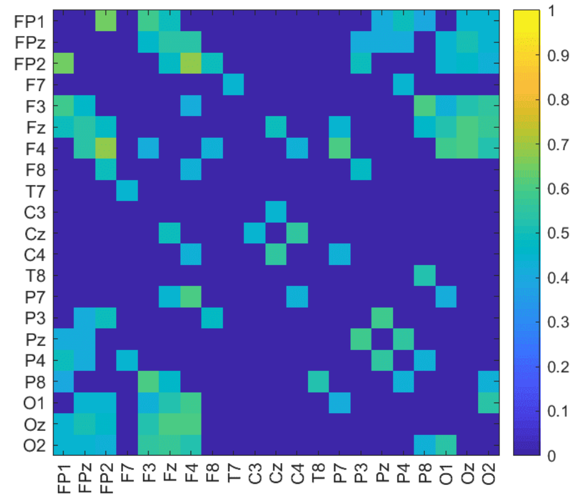
Figure A.31: Adjacency matrix of PLI-based team brain network.



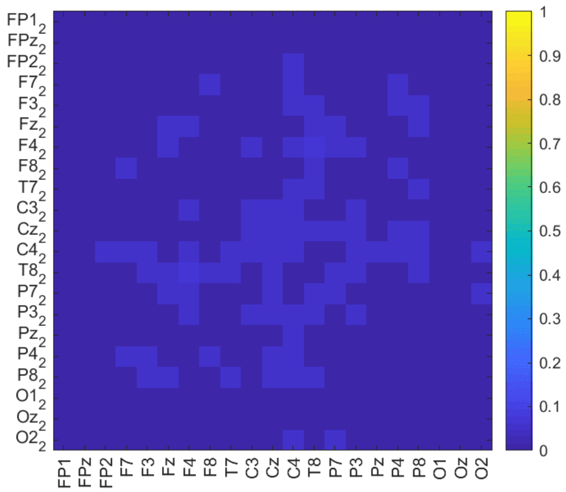
(a) Adjacency matrix of spectral-coherence-based intra-brain network during competitive interaction



(b) Adjacency matrix of spectral-coherence-based inter-brain network during competitive interaction



(c) Adjacency matrix of spectral-coherence-based intra-brain network during co-operational interaction



(d) Adjacency matrix of spectral-coherence-based inter-brain network during co-operational interaction

Figure A.32: Adjacency matrix of spectral-coherence-based team brain network.

A.3.2 Statistically significant Inter-Brain Synchrony

Fig.A.33 illustrates statistically significant PLI-based INS between cooperation and competition. Player A's FP1 electrode behaves mostly differently in INS during these two conditions.

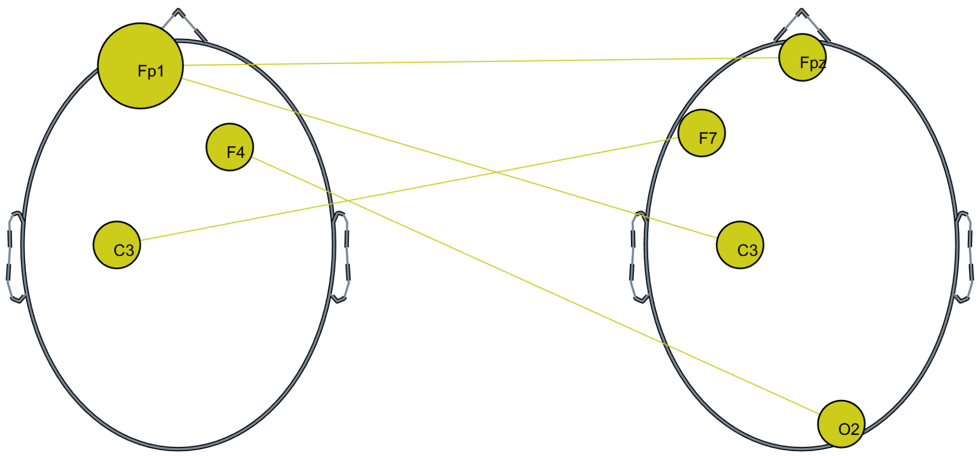


Figure A.33: Statistically significant PLI-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. C3 and C4 are the two largest nodes.

Fig.A.34 illustrates statistically significant power-correlation-based INS between cooperation and competition. Brain signals at player A's C3 and player B's C4 electrodes behave mostly differently in INS during these two conditions.

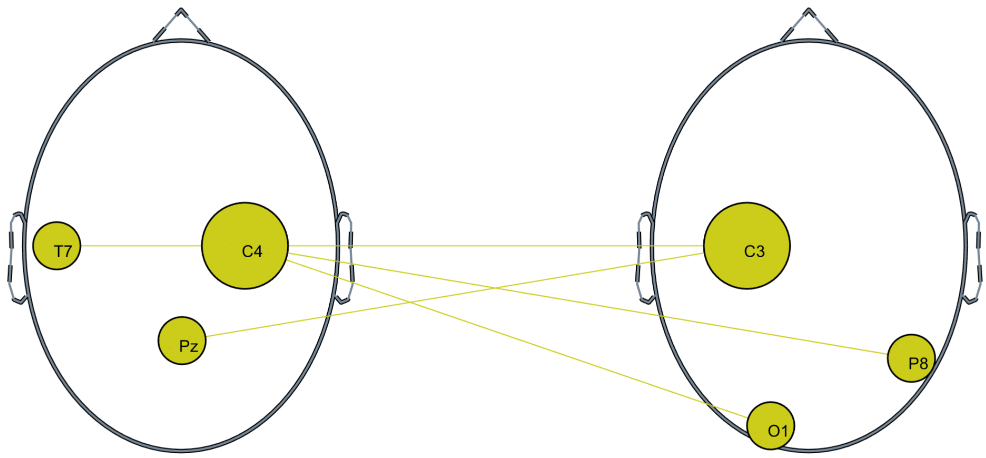


Figure A.34: Statistically significant power-correlation-based INS are illustrated for cooperation vs. competition.Node size positively correlated with its degree. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large. P3,Oz,C3,C4 are the largest nodes.

Fig.A.35 illustrates statistically significant power-correlation-based INS between cooperation and competition. Brain signals at player A's P3, Oz and player B's C3,C4 electrodes behave mostly differently in INS during these two conditions.

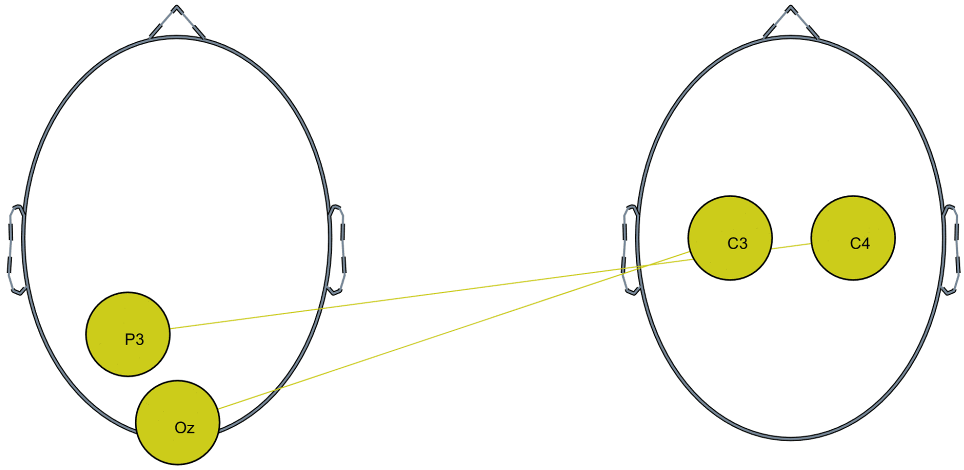


Figure A.35: Statistically significant ISPC-based INS are illustrated for cooperation vs. competition. Lines represent statistically significant INSs. Node represent electrode. Node has more links are more large.

For MI-based and spectral-coherence-based INS, there is no statistically significant INS during cooperation and competition.

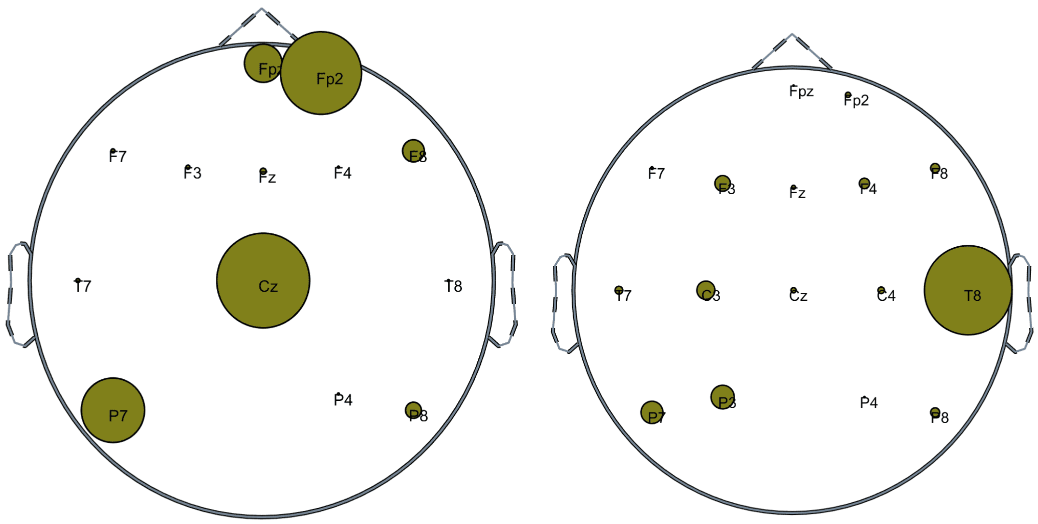
A.3.3 Brain Hubs

Fig.A.36a and Fig.A.36b illustrate the brain hubs of ISPC-based team brain network during competition and cooperation respectively. Fp1, Cz, P7 are three hubs of the team brain network during competition while T8 is the hub for cooperation.

Fig.A.37a and Fig.A.37b illustrate the hubs of power-correlation-based team brain network during competition and cooperation respectively. C3, Cz, T8,P7,P8 and Fz are three hubs of the team brain network during competition while T8 and P3 are the hubs for cooperation.

Fig.A.38a and Fig.A.38b illustrate the hubs for spectral-coherence-based team brain network during competition and cooperation respectively. Fp2 are three hubs of the team brain network during competition while F3 and T8 are the hubs for cooperation.

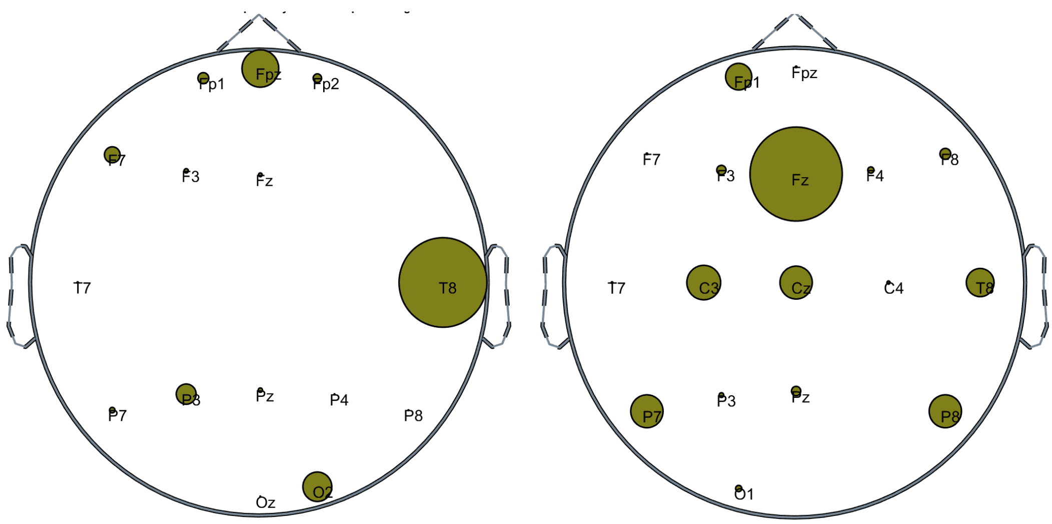
For MI-based and PLI-based team brain networks, there is no hubs (which is measured by betweenness centrality).



(a) Hubs of the ISPC-based team brain network during competition

(b) Hubs of the ISPC-based team brain network during cooperation

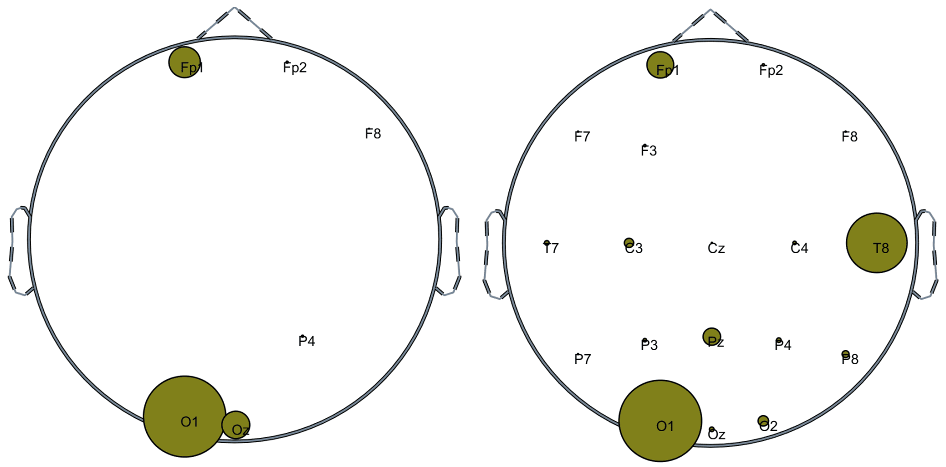
Figure A.36: Illustration of hubs of ISPC-based team brain network on cooperative/competitive interaction. Hubs were measured by betweenness centrality.



(a) Hubs of the power-correlation-based team brain network during competition

(b) Hubs of the power-correlation-based team brain network during cooperation

Figure A.37: Illustration of hubs of power-correlation-based team brain network on cooperative/competitive interaction.



(a) Hubs of the spectral-coherence-based team brain network during competition

(b) Hubs of the spectral-coherence-based team brain network during cooperation

Figure A.38: Illustration of hubs of spectral-coherence-based team brain network on cooperative/competitive interaction.

A.3.4 Topological Properties

Global Efficiency

Tab.A.3 shows GE of the team- and intra-brain networks.

	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.3618	0.3447	0.4856	0.4682
Power-correlation	0.2474	0.2513	0.5578	0.3559
Spectral-coherence	0.1831	0.1768	0.6816	0.3263

Table A.3: GE of team- and intra-brain networks

Small-World-Ness

Tab.A.4 shows the SWN for the team and intra-brain networks.

	Team-brain network		Intra-brain network	
FC method	Competition	Cooperation	Competition	Cooperation
ISPC	0.9423	0.9906	0.9358	0.9453
Power-correlation	1.2525	1.1917	0.9352	1.0505
Spectral-coherence	1.6240	1.8794	0.8973	1.1306

Table A.4: SWN of team- and intra-brain networks

A.4 Experimental Protocol

A.4.1 Background

Neural activity can be quantified by recording and analyzing the EEG signal. In order to test team neurodynamics, dyads were required to play cooperative/competitive computer pong-game. The materials required for such an experiment and the step-by-step protocol is described next. The setup of the experiment is illustrated in Fig.A.39.

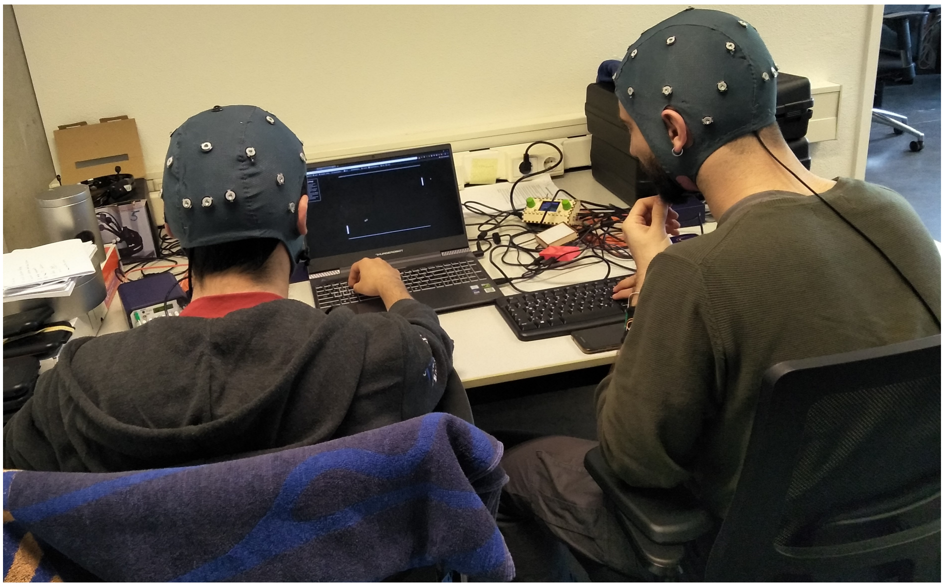


Figure A.39: Two subjects sat alongside with each other and played cooperative/-competitive computer pong-game together. One subject used an external keyboard to control the game.

A.4.2 Required Materials

description	#	specification
general		
computers	1	One computer with Openvibe acquisition and Openvibe designer software. The computer should have at least two USB ports.
external keyboard	1	One external keyboard that can share the keyboard with the computer
USB hub	1	USB hub should at least have two ports
USB hub cable	1	The USB hub cable is used to connect a USB hub with the computer
towel	2	Towel should be clean and dry. They are offered to two subjects after experiment to clean up their hair.

toothbrush	1	This is used to clean gel in EEG caps after experiments
EEG Measurements		
porti device	2	The data acquisition device (Porti Amplifier) with one ground input, one trigger input, one power connector and 34 patient connections (unipolar, bipolar, auxiliary or saturation)
optical fiber	2	Glass fiber used to provide isolation from the PC to the patient
Fusbi	2	Module used as interface between glass fiber and USB cable
power supply	2	Power supply to be used when thee device is powered via mains
USB cable	2	Usb cable to connect Fusbi to the PC
EEG caps	2	TMSI 32-channel low-noise actively shielded caps. Two median, one small and one large caps are available for different head size of the subjects
EEG electrode gel	200ml	Electro-gel(ECI), for injection in EEG cap electrodes
power cable	2	Power cable to be used in combination with power supply
comfortable chair	2	Comfortable chair for subjects to relax during the experiment. The chair should especially provide rest to the muscles around the head and the neck, since those might disturb the measurement.

A.4.3 Procedure

General Preparation

Time: > 1 day before experiment

1. Send the consent form with experiment information (which is attached in AppendixA.4.4) and demographic questionnaire (which is attached in AppendixA.4.4) to participants by email. Tell them:

    (a) The date, time and location of the experiment

    (b) Abstaining from alcohol for at least 24 hours before the experiment

    (c) Drinking the same amount of coffee that they would normally drink on any other day

2. After dates and time for the experiments have been planned, inform the subject about the decided dates and time.

3. Make sure that the EEG equipment work well

Apparatus preparation

Time: > 0.5 hours before experiment

EEG system

1. Set up experiment equipment.

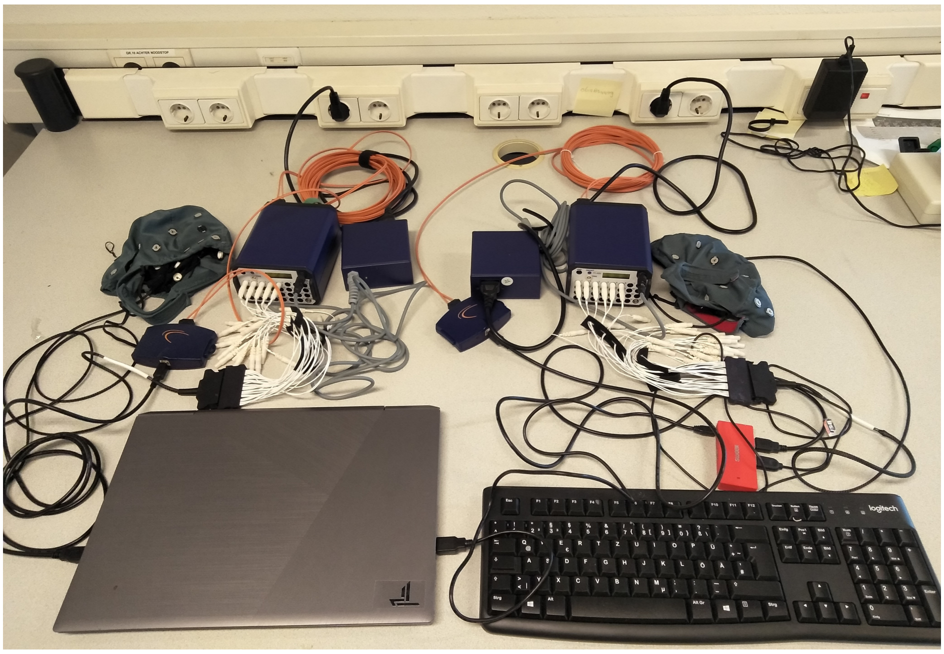
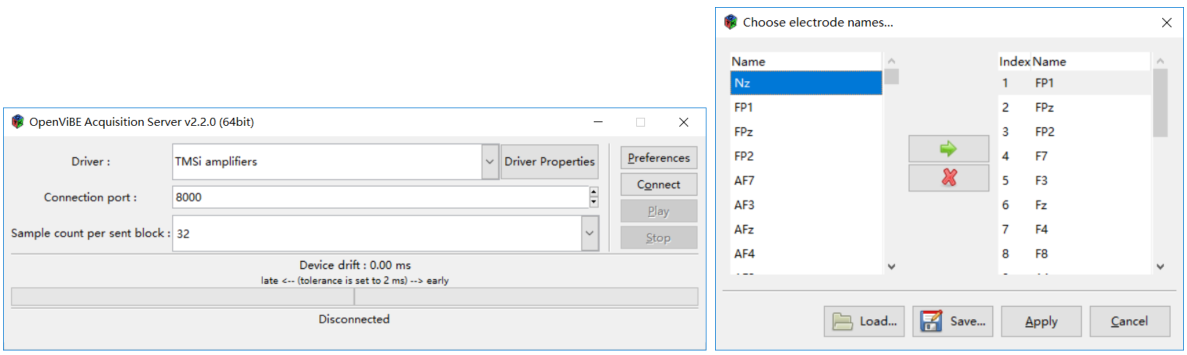


Figure A.40: Equipment setting-up
Equipment setting-up. Two TMSI equipment were connected to one PC. An external keyboard was also connected to the PC with the red USB hub.



(a) Driver and connection port setting of the OpenVibe acquisition window

(b) Maps between electrode name and index

Figure A.41: OpenVibe acquisition server setting-up

OpenVibe software

1. Open two Openvibe acquisition windows. As shown in Fig.A.41a, ”TMSI amplifiers” is chosen as ”Driver” and connection port are 1024 and 15361 for two acquisition windows. Click on ”Driver Properties”, choose the right USB device on the Driver Settings section. On ”Channel Settings” section, set the ”number of EEG channels” into 23, and click ” Change EEG channel names” button. From index 1 to 23, the corresponding electrode names are: Fp1,Fpz,Fp2,F7, F3,Fz,F4,F8,A1,T7,C3,Cz,C4,T8,A2,P7,P3, Pz,P4,P8,O1,Oz and O2, as shown in Fig. Click ”Apply” on node selection window and click ”Apply” on TMSI Universal Driver window. Click ”Preferences” to open global configuration window, change ”TCP_Tagging_Port” into 8080 and 8000. Click ”Apply” to close global configuration window. Click ”connect” to connect TMSI with PC.

2. Open two OpenVibe designer scenarios. One scenario is shown in Fig.A.42. In ”Acquisition client” box. acquisition server ports are 1024 and 15361 for two TMSI EEG equipment.

3. Click ”connect” on two opened OpenVibe acquisition windows to check TMSI connected well with PC.

4. Click on ”execute” on two OpenVibe Designer scenarios to make sure real-time EEG signals can be shown on screen and saved locally.

5. Check trigger-listening files. Run $Tcp\_tagging.py$ file (shown in Sec.A.4.5), which listens key-pressing on 8080 port and sends simulations into OpenVibe designer scenarios.

6. If all equipment work well:
   - Click ”disconnected” on two OpenVibe software windows.
   - Click ”stop” on two OpenVibe designers scenarios.
   - Stop running $tcp\_tagginng.py$ files

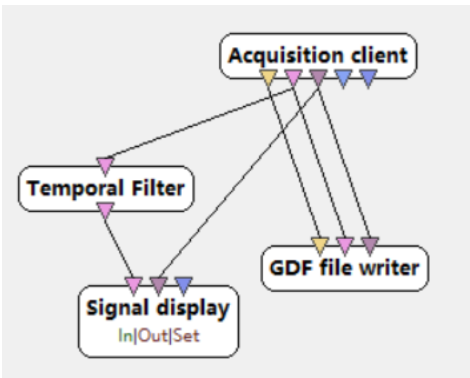


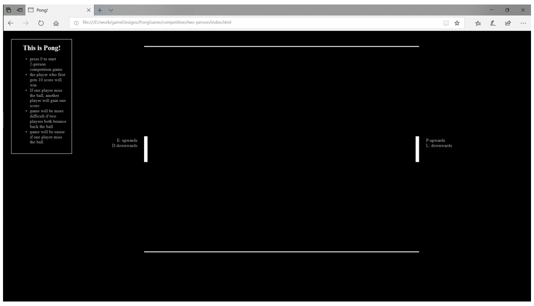
Figure A.42: Screen-shot of the OpenVibe designer scenario.

Pong-game

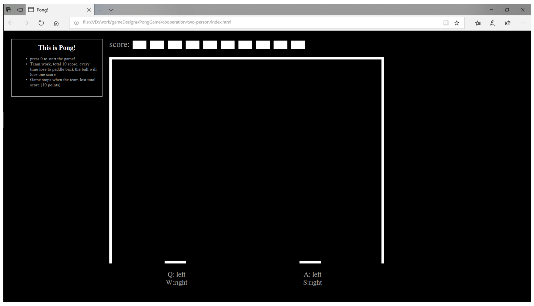
1. Open cooperative and competitive web pong-game. Game files are shared on github. Two-person cooperative and competitive pong-games are also published online. Fig.A.43a and Fig.A.43b show the competitive and cooperative pong-game respectively.

2. Check pressing corresponding keys controls game very well on two keyboards.

3. If pong-games work well, press F5 to refresh the web-pages.



(a) Competitive computer pong game. Press 0 to start the game. Press key E and D to control left paddle to move up and down. Press key P and L to control right paddle to move up and down. Left and right paddle need to bounce ball back. If the left paddle miss a ball, the player who controls the right paddle will win one score.The person who first win ten score will win this game and end this game.



(b) Cooperative computer pong game.In this game,press Q and W to control the left paddle move left and right respectively. Key A and S controls the right paddle to move left and right respectively. Each paddle can only move on the half side of the court((s.t., the left paddle can only move within the left half court). In this game, the team has total 10 scores, which are shown on the top of the court. Every-time the team miss a ball, they will lose a score. When the team lose all 10 times, the game ends.

Figure A.43: Competitive/cooperative computer pong game

Materials Preparation

Time: $>$ 0.25 hours before experiment make sure that the following materials are ready for use an easy to reach:

1. Electrode caps

2. EEG electrode gel

3. Needles

subject Reception and Preparation

Time: start of the session.

1. Be present at the lab entrance ten minutes before the session to receive the subject and lead them into the lab.

2. Give the subject a hard copy of the information letter (of which they have received and read a soft-copy in advance, preferably) and the consent form.

3. Ask the subject:

   - ”have you read the information carefully?”
   - ”Do you have any questions?”

4. Instruct the subject to fill in and sign a consent form if they would like to participate in the experiment

5. Explain to the subject that the experiment will now begin and will take approximately one hours. Instruct the subject:

   - ”Make sure of the toilet if you need to, as the session will last for an uninterrupted one hours”
   - ”Please turn off your phone or put it on the Airplane Mode” IMPORTANT: Turn your own phone on airplane mode as well.

6. Seat the subject in the designated chair and instruct them:

   - ”Please sit in a comfortable position, The seat can be adjusted using the buttons on the side.”
   - ”Make sure there is enough space for your legs.”
   - ”Incline the chair backwards to relieve tension in the neck muscles”

7. Place the appropriate electrode cap on the subject’s head, pulling it back from the forehead.

8. Instruct the subject:

   - ” Please fasten the cap strap under your chin as tightly as comfortably possible”
   - ”Please use the tightening string given on the side to ensure a better fit.”

9. Measure the distance between the nasion and the inion, and the distance between the two post-auricular points.

10. Check if the Cz electrode is exactly at the center of the measured distances and adjust the cap if required.

11. Attach the EBA multi-connectors of the EEG cap to the inputs of the EEG amplifier. The connectors are numbered in $1, 2, 3, 4, 5, 6, 7, 8, 13, 14, 15, 16, 17, 18, 19, 24, 25, 26, 27, 28, 30, 31, 32$ and they correspond to the input number from 1 to 23 respectively.

12. Attach the connectors of wrist-bands to the inputs of ground-signal in the EEG amplifier.

13. Explain the next part to the subject:

    - ”Gel will now be injected into the electrodes on your head using a blunt needle.”
    - The needle will be used to scratch your skin and move hair out of the way, for better connectivity. This should not hurt; in case it does hurt, please say no”
    - ”If you feel any discomfort at any point, you can indicate this immediately.”

14. Take a new needle from the packet and show this to the subject. Attach the needle to the syringe and fill the syringe with gel.

15. Fill each electrode in the EEG cap with gel, by first scratching the skin and moving hair using a large circular movement. Make sure to extract the needle slowly while injecting the gel to avoid gel from squeezing out from the sides and causing cross-connections between electrodes.

16. Use the impedance display on the screen to ensure that all impedance are below $5k\Omega$.

17. Click on ”connect” button on two OpenVibe acquisition windows

18. Click ”execute” button on two openVibe designer scenarios. If two signals are being measured correctly, 23 labeled brain signals should be seen on the screen.

19. click ”stop” button on two Openvibe designer scenario after checking data quality.

Familiarization

Time: 30 minutes after the start of session

1. Explain to the subjects

    - ”You will play 8 rounds of pong-game. For each round, I will record your brain signal, video the computer screen.”
    - ” I will press 0 to start the pong game. When the game starts, you should hold still and only move your two fingers to control the game. After the game ending, I will press F5 to stop this game round. ”

2. Explain the game rule to two subjects

    - ”For the cooperative computer pong-game, you two subjects are working as a team to control two paddles to hit the ball back. You have 10 score at the beginning, which is shown on the top of the court, and each time you lose a ball, your team will miss a score. Key A and S control the right paddle to move left and right while Key Q and W control the left paddle to move left and right. Each paddle can only move half of the court, for example, the left paddle can only move within the left half side of the court. The game will end if your team lose all ten scores. There are 4 rounds for cooperative game, and during these 4 rounds, your team are allowed to talk strategy with each other about how to improve team performance. ”

- ”In competitive pong-game, you two subjects are competitors to each other. Ky E and D control the left paddle to move up and down. Key P and L control right paddle to move up and down. If the left paddle miss a ball, the player who controls the right paddle will win one score. The person who first win ten scores will win this game.

3. Explain the familiarization procedure to the subject:
   - ”The first part of the experiment is to get you acquainted with the pong-game, so that you know what to expect during the actual experiment.”
4. Press key 0 to start the cooperative pong game for one round. Allow them to discuss the cooperation strategy.
5. Press key 0 to start the competitive pong game for one round. IMPORTANT: shuffle cooperative and competitive pong games order for different teams.

Experiment

Time: 40 minutes after the start of session

1. Explain the experimental procedure to the subject:
   - ”To record precisely, I will say please prepare the game before I press key 0 to start the game”
   - ”In case you need a short break or want to talk (ask questions), you can press F5 to stop the game and this trial will be dropped.”
2. Instruct the subject:
   - ”Please keeping you focused on the game, do not distract, as far as possible.”
   - ”Try to blink as few times as possible while playing this game”
   - ”Try to relax; also relax your muscles, especially the reference arm”
   - ”Do not talk or move while playing the game. In case you have/need to, press F5 to stop the game and this trial will be dropped”
   - ”Following these instructions will greatly enhance the quality of the signals measured, and thereby of the result.”
3. When the subjects are both ready:
   (a) Press screencastify icon (chrome extension) on the chrome to start video screen

(b) Press ”execute” icons to execute two openVibe designer scenarios to record and display signals on real-time

(c) Run ”python $tcp_tagging_8000.py$” and ”python $tcp_tagging_8080.py$ two files to listening key pressing event on 8000 and 8080 port.

(d) Press 0 to start the game.

4. When the game ends:

   (a) Press F5 to stop the game immediately.

   (b) Press ”stop” on two Openvibe Designer scenarios.

   (c) Press screencastify icon on the chrome toolbar to stop screen-videoing.

5. This process has to be repeated for each round. After each round of cooperative game, the subjects are required to talk with each other about game strategy to improve game performance.

Closure

1. Inform the subject that the experiment was completed successfully.
2. Disconnect the subject from all the cables.
3. Instruct the subject to take off the EEG cap and hand it over to you.
4. Inform the subject:
   - ” You can wash hair at the sink.”
   - ” You can clean your hair with clean towel.”
5. When the subjects is ready to leave, tell the subject:
   - ”Thank you participating in this experiment”
   - ”Would you like to be informed of the results of the experiment?”
   - ”If you have any questions, please do not hesitate to contact me”
6. Provide the subject with contact information and lead them out of the lab.

Clean-up

1. Turn off the software and the EEG amplifier
2. Clean the cap electrodes directly after the experiment using warm water with toothbrush
3. Hang the cap on the provided fan to dry.
4. Put all the equipment in the proper places.

A.4.4 Files

This section list consent file with experiment information, demographic ad health questionnaire and trigger-listening file.

Consent from

Experiment Information

- The research topic is to analyze teamneurodynamic during cooperational/competitive interaction with EEG
- This is for Qiurui Chen's master thesis.
- Participants are required to play cooperational/competitive computer Pong-games together in two persons with TMSI EEG equipment.
- This research project has been reviewed and approved by the EEMCS Ethics Committee.
- Personal information includes age, gender, name initials and some health information.
- All personal information will keep anonymous. There is no possibility to track down into the participant according the personal information collected.
- EEG data will be recorded during experiment.
- The computer screen will be videoed during experiment
- All data collected will only be used for academic study.
- The participant has the right to request access to and rectification or erasure of personal data.
- The data will be shared to and reused by other researchers for future research studies that may be similar to this study or may be completely different.
- The researcher name is Qiurui Chen, and her email address is q.chen@student.utwente.nl
- To file a complaint, the EEMCS Ethics Committee email address is ethics-comm-ewi@utwente.nl

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Consent Form

team neurodynamic analysis during cooperational and competitive interaction with EEG

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated [__/__/2019], or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that taking part in the study involves	○	○
1. A competitive and cooperational computer pong-game		
2. Demograhic and health form		
I understand that taking part in the study involves the following risks: When recording with EEG, a gel will be applied to your scalp. This leaves a residue on your hair. Gel is not harmful for physical or mental health.	○	○
Use of the information in the study		
I understand that information I provide will be used for Qiurui Chen's master thesis.	○	○
I agree that my information can be quoted in research outputs	○	○

Signatures

______________________ ______________________ ________

Name of participant [printed]

Signature Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_________________________ ___________________ ________

Researcher name [printed] Signature Date

Study contact details for further information: [Qiurui Chen*, q.chen@student.utwente.nl*]

Contact Information for Questions about Your Rights as a Research Participant

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Ethics Committee of the EEMCS at the University of Twente by ethicscommittee-bms@utwente.nl

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demographic and health questionnaire

Please fill this form before game-playing.

1 Participant information

1. Name initials?

   ....

2. Age?

   ....

3. Gender ?

   ☐Female ☐Male

4. Nationality?

   ....

5. Experiment date

   ....

2 Health condition

1. Are you in good health condition ? If not, what's your illness name?
   ☐Yes ☐Not ....

2. Did you have brain surgery before?
   ☐Yes ☐Not

3. Do you take any medicines or drugs that affect to nervous system?
   ☐Yes ☐Not

4. You are
   □left handedness □right handedness

5. Your history of medical and neurologic disease (e.g., Epilepsy, nervous system disease)?
   □Clean □Not clean ....

6. Do you have binge eating disorders and other psychiatric disorders?
   □Yes □Not

7. Do you have head trauma?
   □Yes □Not

8. Do you assumption of Central Nervous System active drugs in the two weeks prior to study entry? (e.g.,benzodiazepines, antidepressants, anticonvulsants, and narcotics)
   □Yes □Not

A.4.5 Trigger-listening file

```
import sys
import socket
from time import time, sleep
import keyboard

HOST = '127.0.0.1'
PORT = 8080

EVENT_START = 0x00008001
EVENT_STOP = 0x00008002
DELAY=0
def to_byte(value, length):
    for x in range(length):
        yield value%256
        value//=256

# connect
s = socket.socket(socket.AF_INET, socket.SOCK_STREAM)
s.connect((HOST, PORT))

def messageSend(event_id):
    padding=[0]*8
    event_id=list(to_byte(event_id, 8))
    timestamp=list(to_byte(int(time()*1000)+DELAY, 8))
    s.sendall(bytearray(padding+event_id+timestamp))


while True:
    try:
        if keyboard.is_pressed('0'):  # game start
            messageSend(EVENT_START)
        elif keyboard.is_pressed('f5'):  # end of the game
            messageSend(EVENT_STOP)
        else:
            pass
    except:
        break

s.close()
```

A.5 Literature Overview on Cooperation and Competition

Author	Study Focus	Findings
Balconi, Michela et al. [5]	feedback influence on competition	1. performance improved with respect to control conditions (reinforcing feedback) 2. a reduction of inter-brain functional connectivity (primarily involving bilateral prefrontal areas) for slower EEG frequency bands (Delta and theta) 3. a significant association between cognitive performance and inter-brain connectivity measures
Balconi, Michela at al. [7]	cognitive strategies influence in cooperation & competition	1. functional connectivity and cognitive performance were considered during joint which was failing 2. reduced inter-brain connectivity was found after negative feedback 3. cognitive performance was modulated by joint-action and external feedback 4. DLPFC was revealed to support negative feedback processing
Balconi, Michela et al. [8]	neural patterns in competition	1. increased brain-to-brain coupling and improved cognitive outcomes due to joint-action and the competition 2. an increased brain activity in the prefrontal cortex (PFC) in post-feedback condition than pre-feedback 3. a significant increased prefrontal brain lateralization effect was observed for the right hemisphere
Balconi, Michela et al. [2]	personality influence in competition& cooperation	1. An increased left prefrontal cortical (PFC) responsiveness was found for subjects who had higher behavioral activation system (BAS) rating (more self motivated) in the case of both cooperation and competition conditions. 2. subjects with higher BAS ratings showed greater frontal left activity during the cooperation task; these subjects also concomitantly perceived an increasing in social ranking and improved their performance

Zhang, Dandan et al. [17]	belief on cooperation	1. At the individual level, the amplitudes of the ERP components frontal P3a and parietal P3b elicited by the decision outcome were sensitive to belied updating 2. at the interpersonal level, the between-subject synchronization in P3b was higher than those in the other conditions when the paired participants confirmed each other's reciprocal beliefs. 3. suggest that a cooperative relationship is built up when the memory system (which support belief updating) of two interacting person reach a high level of coordination
Hu, Yi et al. [32]	decision making on cooperation	1. EEG hyperscanning is performed during interactive decision making 2. inter-brain synchrony increases under the context of high cooperation index in the human-human condition 3. inter-brain synchrony during decision making is related to cooperative interaction 4. inter-brain synchrony during decision making depends on cooperation context
Golland, Yulia et al. [15]	emotion x	1. the autonomic signals of co-present participants were idiosyncratically synchronized and that the degree of this synchronization was correlated with the convergence of their emotional response 2. moment-to-moment emotional transitions, resulting in shared emotional experiences, can occur in the absence of direct communication and are mediated by autonomic synchronization
Michela Balconi et al. [1]	personality influence on cooperation	1. higher Behavioral Activation System (BAS) participants and higher internal locus of control (LoC) responded in greater measure to post-feedback condition with better real performance probably based on their sensitivity to rewarding for high-BAS and the increased sense of self-efficacy 2. higher-BAS showed an increased frontal left activity when they perceived increased cooperative efficacy.

Balconi, Michela et al. [9]	joint strategy influence on cooperation	1. A worse performance after the negative feedback in the form of longer reaction times and a specific pattern of brain activation involving the dorsolateral prefrontal cortex (DLPFC) and the superior frontal gyrus. 2. The DLPFC showed increased O2Hb (oxy-haemoglobin) level after the feedback, compatible with the need for higher cognitive effort 3. A decreased inter-brain synchronicity in post-feedback condition for the dyad 4. The representation of negative emotions in response to failing interactions was signalled by a right-lateralized effect
Balconi, Michela et al. [10]	strategic cooperation	1. the external feedback could modulate participant responses in both behavioral and neural components. 2. After the reinforcing manipulation, there were faster response times and increased inter-brain connectivity 3. Neural synchrony emerged primarily over the dorsolateral prefrontal cortex 4. additionally, the presence of significant correlations between response times and inter-brain connectivity revealed that only the ”two-players connection” may guarantee an efficient performance
Balconi, Michela et al. [1]	efficient/inefficient cooperation	1. the behavioral performance was affected by feedback valence, since the negative feedback induced a significant worse performance in contrast to the positive one, which significantly increased performance 2. data from functional near-infrared spectroscopy (fNIRS) showed a specific lateralization effect with the right DLPFC recruited in the case of negative feedback ,and an opposite left-sided effect in the case of a positive feedback 3. inefficient condition could be similar to a competitive context since the perception of a failed joint action could have frustrated the cooperative attitude and the use of joint strategies

Balconi, Michela et al. [11]	joint actions in cooperation	1. the shared cognitive strategy was concurrently-improved within the dyad after social reinforcing 2. fNIRS measures revealed an increased brain activity in the post-feedback condition for the dyad 3. an inter-brain similarity was found for the dyads during the task, with higher coherence prefrontal cortex (PFC) activity for the interagents in the post-feedback condition 4. a significant prefrontal brain lateralization effect was revealed, with the left hemisphere being more engaged during the post-feedback condition 5. the self-perception, cognitive performance, and the shared brain activity were all reinforced by the social feedback within the dyad.
Robinson, Bradley et al. [18]	neural patterns on cooperation & competition	1. greater beta (12-24Hz) activation in the dorsolateral prefrontal cortex (DLPFC) when participants defect; there is a greater general amount of activated to defection as compared with cooperation. 2. In Snowdrift and Prisoner's Dilemma game, cooperation showed a decreased alpha desynchronization compared with defection
Balconi, Michela et al. [12]	joint action in behavioral synchrony	1. the induced feedback affected both the cognitive performance and brain-to-brain coupling by increasing behavioral and brain synchronization when a positive feedback was furnished to the participants for their performance 2. About the cortical contribution, high coherence effect was mainly observed when a positive reinforcers was procedure, but only for some low frequency bands with the prefrontal left area, compared to the right one 3. the cognitive and EEG coherence measures were shown to be correlated with a significant similar trend anchored to the progressive feedback

Liu, Tao et al. [20]	role of the right inferior frontal gyrus cooperation and competition	The builder's activation in the right IFG is reduced/increased in the context of interacting with a cooperative/competitive partner
Apanovich, V.V. et al. [34]	event-related potentials in cooperation and competition	1. Both behavioral performance and physiological measures exhibited higher variance in holistic than in analytic subjects. 2. Differences in amplitude and P300 latency suggest that decision making was easier for the holistic subjects in the cooperation condition, in contrast to analytic subjects for whom decision making based on these measures seemed to be easier in the competition condition. 3. the brains of analytic and holistic subjects work differently in different types of social interaction conditions
Balconi, Michela et al. [13]	joint strategies in cooperation	1. Worse behavioral outcomes emerged, with longer response times with respect to the pre-feedback one. 2. In parallel, a specific right-lateralized effect was observed over the dorsolateral prefrontal cortex (DLPFC), with increased delta and theta power compared to the previous condition.
Cui, Fang et al. [81]	neural response to others' pain during cooperation & competition	the participants were more responsive to other's pain in a competitive context than in a co-operative context.
Hariharan, Anuja et al. [16]	cognitive workload & emotional arousal influence on cooperation& competition	1. Cognitive workload was associated negatively with performance in the competitive but not the cooperative model 2. Arousal was associated negatively with performance in the cooperative mode but not the competitive mode

Sinha, Nishant et al. [46]	INS on cooperation& competition	1. the inter-brain synchrony between the subjects was significantly higher when they cooperated with each other as compared to the competitive scenarios 2. inter-brain synchrony was significantly enhanced when the subjects were physically separated i.e., they cooperated via an intranet network
Balconi, Michela et al. [14]	personality effects on competition	1. Higher-BAS participants responded in greater measure to perceived higher cognitive performance (post-feedback condition), with increased left prefrontal activity, higher ranking perception and a better real performance (reduced reaction times) 2. the hemispheric effect in favor of the left side characterized the competitive behavior, showing an imbalance for high-BAS in comparison to low-BAS in the case of a rewarding (post-feedback) context.
Xue, Hua et al. [6]	creativity influence on cooperation	1. Dyads consisting of two less-creative members could perform as well to dyads consisting of highly-creative individuals 2. stronger interpersonal brain synchronization (IBS) between group members as evoked in the low-low dyads. 3. The IBS in rDLPFC and rTPJ co-varied with the creative performance and cooperation in the low-low dyads 4. the better cooperation in the low-low dyads (indicated by behaviour index and IBS) may account for the enhanced performance
Piva, Matthew et al. [82]	neural patterns during competition	A frontal-parietal neural complex including the TPJ, dlPFC, SCA,SS and FG that is more active during human-to-human social cognition both within brains (functional connectivity) and across brains (across-brain coherence), as compared with human-to-computer condition.
Balconi, Michela et al. [33]	neural patterns when cooperation fails	1. cooperation increases cognitive performance and functional connectivity 2. social feedback affects brain connectivity and cognitive performance3. negative feedback induces increased intra-brain connectivity and decreased inter-brain connectivity

Osaka, Naoyuki et al. [83]	cooperative singing	1. a significant increase in the neural synchronization of the left inferior frontal cortex (IFC) for cooperative singing or humming regardless of face-to-face or face-to-wall compared with singing or humming alone. 2. the right IFC showed an increase in neural synchronization for humming only, possibly due to more dependent on musical processing
Lu, Kelong et al. [19]	creativity effects on cooperation	1. The fNIRS data revealed increased (task-baseline) interpersonal brain synchronization (IBS) in the right dorsolateral prefrontal cortex (rr-DLPFC) and r-TPJ, only for dyads in the cooperation condition 2. A stronger IBS was evoked between the regions in prefrontal and posterior temporal regions in the cooperation condition, as compared with the competition mode.

Table A.6: Overview of neural studies on cooperation/competition

A.6 Team-coordination studies overview

Author	Year	Paradigm	Equipment	Findings
Baker, Joseph M. et al. [64]	2016	cooperation (computer-based cooperation task with different gender setting)	fNIRS	1. Dyads containing at least one male demonstrated significantly higher behavioral performance than female-female dyads. 2. Individual males and females showed significant activation in the right frontopolar and right inferior prefrontal cortices, although this activation was greater in females compared to males. 3. Female-female dyads exhibited significant inter-brain coherence within the right temporal cortex, while significant coherence in male-male dyads occurred in the right inferior prefrontal cortex. 4. Significant coherence was not observed in mixed-sex dyads. 5. For same-sex dyads only, task-related inter-brain coherence was positively correlated with cooperation task performance.
Nozawa, Takayuki et al. [84]	2016	cooperation (Japanese cooperative word-chain game communication)	fNIRS	1. Communication enhanced frontopolar INS 2.Removal of the skin blood flow component engenders substantial improvement in sensitivity to communication-enhanced INS and segregation from artifactual synchronization
Zhang, Mingming et al. [85]	2017	Competition (gambling card-game)	fNIRS	1. Superior temporal sulcus (STS) is uniquely involved in deception but not in honesty, especially in females. 2. the STS may play a critical role in spontaneous deception due to mentalizing requirements relating to modulating opponents' thoughts.
Stevens, Ronald et al. [86]	2016	cooperation (ventilation simulation)	EEG	Neurodynamic and communication measures of team organization may be valuable tools for understanding and assessing the short term dynamics of teams during simulation training, complementing and extending observational evaluations of teams.

Liu, Tao et al. [20]	2015	cooperation (computer-based turn-taking disk game)	NIRS)	1. the builders activation in the right inferior frontal gyrus (IFG) is reduced/increased in the context of interacting with a cooperative/competitive partner. 2.The competitor may have deeper mind-set synchronization in the competition condition, while the cooperator may have shallower mind-set synchronization in the cooperation condition.
Stevens, Ronald and Galloway, Trysha [87]	2014	cooperation (an map navigation)	EEG	Neurodynamics reorganizations occurred in teams in response to multiple types of perturbations, but primarily when the team perceived difficulties
Babiloni, Claudio et al. [88]	2011	cooperation (watching show and playing saxophonist afterwards)	EEG + EOG + EMG	1. the higher the empathy quotient test score, the higher the alpha desynchronization in right Brodmann Area (BA) 44/45 during the OBSERVATION referenced to RESTING condition. 2. Empathy trait score and alpha desynchronization were not correlated in other control areas or in EXECUTION/CONTROL conditions result: alpha rhythms in BA 44/45 reflect emotional empathy in musicians observing own performance.
Stikic, Maja et al. [89]	2013	cooperation (a case problem)	EEG	1. quantitative EEG could be effectively used in the team settings as an estimator of individual and team engagement, as well as the leadership qualities shown by team members. 2. that EEG can help in understanding, and perhaps building, optimal teams and team processes.

Lin, Xiao-hong and Sai, Liyang and Yuan, Zhen [90]	2018	cooperation (a modified concealed information test (CIT) task)	EEG + fNIRS	results: 1. for the guilty group, the probe stimulus elicited significantly higher P300 amplitude at parietal site and also evoked significantly stronger oxyhemoglobin (HbO) concentration changes in the bilateral superior frontal gyrus and bilateral middle frontal gyrus than the irrelevant stimuli 2. the combined ERP and fNIRS feature was able to differentiate the guilty and innocent groups with enhanced sensitivity, in which AUC (the area under Receiver Operating Characteristics curve) is 0.94 for deception detection based on the combined indicator, much higher than that based on the ERP component P300 only (0.85) or HbO measure only (0.84).
Xue, Hua et al. [6]	2018	cooperation (a realistic presented problem)	fNIRS	results: when two less-creative individuals worked on a creativity problem together, they tended to cooperate with each other (indicated by both behaviour index and increased IBS at rDLPFC and rTPJ), which benefited their creative performance.
Astolfi, Laura et al. [91]	2010	cooperation (card games)	EEG	we proposed the use of a modified functional connectivity estimator to assess Granger-causal relationships between the signals estimated in ROIs of different subjects.
Cui, Xu et al. [26]	2012	cooperation (computer-based co-operation game)	NIRS	1.The coherence between signals generated by participants' right superior frontal cortices increased during cooperation, but not during competition. 2. Increased coherence was also associated with better cooperation performance.

Balconi, Michela et al. [10]	2017	cooperation (computer-based co-operation game)	fNIRS	1. positive feedback is possible to induce improved behavioral performance 2. the engagement of DLPFC after social feedback can be referred to as the adoption of joint strategies, while the increased connectivity between homologous DLPFC in intra-brain analysis can suggest the general recruitment of a neural network for the joint task. 3. a brain-to-brain coupling induced by a cooperative task may be directly associated with a significantly improved performance.
Cheng, Xiao-jun et al. [92]	2015	cooperation (computer-based games with different gender setting)	fNIRS	1. Cooperation was greater in malemale pairs than in femalefemale pairs, with intermediate cooperation levels for femalemale pairs. 2. More importantly, in dyads with partners with opposite gender (female-male pairs), we found significant task-related cross-brain coherence in frontal regions (i.e., frontopolar cortex, orbitofrontal cortex, and left dorsolateral pre-frontal cortex) whereas the cooperation in same gender dyads (femalefemale pairs and malemale pairs) was not associated with such synchronization. 3. Moreover, the changes of such interbrain coherence across task blocks were significantly correlated with change in degree of cooperation only in mixed-sex dyads.results: that different neural processes underlie cooperation between mixed-sex and same-sex dyadic interactions
Stevens, Ronald H et al. [93]	2014	cooperation	EEG	The expression of different neurophysiologic synchrony patterns is sensitive to changes in the behavior of teams over time and perhaps to the level of expertise.

Kinreich, Sivan et al. [66]	2017	cooperation (fun-day planning)	EEG	1. Neural synchrony was found for couples, but not for strangers, localized to temporal-parietal structures and expressed in gamma rhythms. 2. Brain coordination was not found during a three-minute rest, pinpointing neural synchrony to social interactions among affiliative partners. 3. Brain-to-brain synchrony was linked with behavioral synchrony. 4. Among couples, neural synchrony was anchored in moments of social gaze and positive affect, whereas among strangers, longer duration of social gaze and positive affect correlated with greater neural synchrony. 5. Brain-to-brain synchrony was unrelated to episodes of speech/no-speech or general content of conversation result: link brain-to-brain synchrony to the degree of social connectedness among interacting partners, ground neural synchrony in key nonverbal social behaviors, and highlight the role of human attachment in providing a template for two-brain coordination.
Schippers, M. B. et al. [94]	2010	cooperation (game of charades)	fMRI	a guessers brain activity in regions involved in mentalizing and mirroring echoes the temporal structure of a gesturers brain activity result: provides evidence for resonance theories and indicates a fine-grained temporal interplay between regions involved in motor planning and regions involved in thinking about the mental states of others

Reindl, Vanessa et al. [27]	2018	cooperation (game play with different persons)	fNIRS	1. During cooperation, parent's and child's brain activities synchronized in the dorsolateral prefrontal and frontopolar cortex (FPC), which was predictive for their cooperative performance in subsequent trials. 2. No significant brain-to-brain synchrony was observed in the conditions parent-child competition, stranger-child cooperation and stranger-child competition. 3. parent-child compared to stranger-child brain-to-brain synchrony during co-operation in the FPC mediated the association between the parent's and the child's emotion regulation, as assessed by questionnaires brain-to-brain synchrony may represent an underlying neural mechanism of the emotional connection between parent and child, which is linked to the child's development of adaptive emotion regulation
Snger, Johanna and Mller, Viktor and Lindenberger, Ulman [95]	2012	cooperation (guitar playing)	EEG	brain mechanisms indexed by phase locking,phase coherence, and structural properties of within-brain and hyper brain networks support interpersonal action coordination(IAC).
Lindenberger, Ulman et al. [96]	2009	cooperation (guitar playing)	EEG	show that interpersonally coordinated actions are preceded and accompanied by between-brain oscillatory couplings.
Stevens, Ronald H. and Galloway, Trysha L. [28]	2014	cooperation (map navigation task)	EEG	The resulting neurodynamic symbol streams had a persistent structure and contained segments of differential symbol expression. The quantitative Shannon entropy changes during these periods were related to speech, performance, and team responses to task changes.

Stevens, Ronald H. and Galloway, Trysha L. [97]	2017	cooperation (map navigation task/SPAN/ health-care simulations)	EEG	Increased neurodynamic organization occurs when a team's operating rhythm can no longer support the complexity of the task and the team needs to expend energy to reorganize into structures that better minimize the "surprise" in the environment.
Babiloni, Claudio et al. [98]	2011	cooperation (music playing together)	EEG + EOG	During the music performance, alpha power density values decreased in amplitude in several cortical regions, whereas power density values enhanced within narrow high-frequency bands.
Kolm, John et al. [99]	2013	cooperation (radio-controlled vehicle games)	EEG	Proposed a five-state Markov model for group and team operation and evolution that has a stronger basis in neurodynamics
Haroush, Keren and Williams, Ziv M. [100]	2015	cooperation (screen games with reward)	floating microelectrode arrays	1. Disrupting cingulate activity selectively biased mutually beneficial interactions between the monkeys but, surprisingly, had no influence on their decisions when no net-positive outcome was possible 2. A group of other-predictive neurons in the primate anterior cingulate essential for enacting cooperative interactions.
Osaka, Naoyuki and Minamoto et al. [83]	2015	cooperation (singing under face-to-face or face-to-wall conditions)	fNIRS	1.The left inferior frontal cortex (IFC) showed a significant increase in the neural synchronization of for cooperative singing or humming. 2. The right IFC showed an increase in neural synchronization for humming only, possibly due to more dependence on musical processing

Stevens, Ronald et al. [101]	2013	cooperation (SPAN/anti-submarine warfare military simulations/map navigation tasks)	EEG	The effects of these disturbances could be rapidly detected by changes in the entropy levels of the team neurodynamics symbol streams
Ciaramidaro, A. et al. [102]	2018	cooperation (third-party punishment experiment)	EEG	1.Third-party punishment is an efficient means of enforcing strong reciprocity and promoting cooperation 2.Greater integration showed between the punisher and receiver when they are likely to be more involved emotionally, irrespective of the emotional valence (injustice or vicarious reward).
Liu, Tao et al. [76]	2017	cooperation (turn-taking computer-based disk-game)	NIRS	1. The right posterior superior temporal sulcus (pSTS) may be commonly involved in both cooperation and competition due to task demands of joint attention and intention understanding, while the right inferior parietal lobule (IPL) may be more important for competition due to additional requirements of mentalizing resources in competing contexts. 2. participants empathy may promote INS in the bilateral inferior frontal gyrus (IFG)across competitors, and in turn affect their competitive performance
Szymanski, Caroline et al. [29]	2017	cooperation (visual search task)	EEG	1. Local phase synchronization and inter-brain phase synchronization were generally higher when subjects attended to a visual search task jointly than individually 2. Phase synchronization constitutes a neural correlate of social facilitation

Mnoret, Mathilde et al. [40]	2014	cooperation (joint action - saucer and cup placing game)	EEG	1. Acting in a social context induced analogous modulations of motor and sensorimotor regions in observer and actor. 2. Sharing a common goal during an interaction seems thus to evoke a common representation of the global action that includes both actor and observer movements
Jiang, Jing et al. [103]	2014	cooperation (leaderless group discussion)	fNIRS	Leader emergence was characterized by high-level neural synchronization between the leader and followers and that the quality, rather than the frequency, of communications was associated with synchronization.
Stevens, Ronald and Galloway, Trysha [30]	2013	cooperation (map navigation task)	EEG	The entropy fluctuations during disruptions differed in magnitude and duration within and across performances, and were associated with qualitative and quantitative changes in team organization.
Stevens, Ronald H. and Galloway, Trysha L. [104]	2016	cooperation (map navigation/ SPAN)	EEG	1.Decreased NS entropy (i.e., greater neurodynamic organization) was prominent in the $\sim$16 Hz EEG bins during problem solving 2.Decreased NS entropy also occurred in the 2040 Hz bins of both teams and was associated with uncertainty or stress. 3.The highest mutual information levels were associated with decreased NS entropy
Gorman, Jamie C. et al. [3]	2016	cooperation (SPAN)	EEG	cross-level exists in team
Gorman, Jamie C. et al. [105]	2013	cooperation (SPAN)	EEG	team communication and team neurophysiology may lead or lag each other at different stages of team training or experience.

Stevens, Ronald H. et al. [106]	2012	cooperation (SPAN)	EEG	Shannon entropy measures of the NS data stream showed decreases associated with periods when the team was stressed and speaker entropy was high.
Stevens, Ronald and Gorman, C [107]	2013	cooperation (SPAN)	EEG	The overall entropy levels of the neurophysiologic data stream are significantly higher for the organizational neurodynamics of teams
Stevens, Ronald et al. [108]	2015	cooperation (SPAN)	EEG	The degree of neurodynamic organization reflects the performance dynamics of the team with more organization being important during the pre-mission briefing while less organization (i.e. more flexibility) important while performing the task.
Stevens, Ronald and Galloway, Trysha [31]	2016	cooperation (SPAN)	EEG	1.Mutual information was present in the gamma EEG band, and elevated levels were distributed throughout the task 2. These discrete periods of synchrony were poorly correlated at zero lag with either changes in the team's neurodynamic organization, or speech patterns.
Stevens, Ronald et al. [109]	2014	cooperation (SPAN)	EEG	Both routine and unexpected activities trigger increased neurophysiologic synchrony / coherence in teams and that periods of persistent synchrony may signal a team being challenged.
Stevens, Ronald et al. [110]	2013	cooperation (SPAN)	EEG	1. The periods of low NS_E entropy represented moments when the teams cognition had undergone significant re-organization 2. Decreases in NS_E entropy were associated with periods of poorer team performance 3. Experienced submarine navigation teams performed better than Junior Officer teams, had higher overall levels of NS_E entropy and appeared more cognitively flexible.

Naeem, Muhammad et al. [111]	2012	coordination (finger tapping with different instructions)	EEG	1. Clear and systematic modulation of mu band activity in the 1012 Hz range as a function of coordination context. 2. In the left hemisphere general levels of alpha-mu suppression increased progressively as one moved from intrinsic through in-phase to anti-phase contexts but with no specific centralparietal focus. 2. In contrast the right hemisphere displayed context-specific changes in the central parietal region. 3. The intrinsic condition showed a right synchronization which disappeared with the in-phase context even as de-synchronization remained greater in the left hemisphere 4. Anti-phase was associated with larger mu suppression in the right in comparison with left at centralparietal region. Such asymmetrical changes were highly correlated with changing behavioral dynamics.
Kawasaki, Masahiro et al. [112]	2018	coordination (finger tapping task)	EEG	Inter-brain synchronization may play an important role in coordinating one's behavioral rhythms with those of others.
Filho, Edson et al. [113]	2016	coordination (face-to-face juggling)	EEG	Task difficulty and jugglers personal skills may influence the features of the hyperbrain network in its shared/integrative and complementary/segregative tendencies. jugglers

Mu, Yan et al. [114]	2017	coordination (coordination games after reading territorial threats related articles)	EEG	1. Individuals are better able to coordinate under high societal threat as compared to low or no threat 2. Interbrain synchrony of gamma band oscillations is enhanced when people are under high threat, and increased gamma interbrain synchrony is associated with lower dyadic interpersonal time lag (i.e. higher coordination)
Osaka, Naoyuki et al. [115]	2014	coordination (face-to-face humming)	fNIRS	1. INS significantly increased in the right inferior frontal cortex during a non-face-to-face humming. 2. The inferior frontal cortex of the right brain plays a critical role in vocal humming
Tognoli, E. et al. [116]	2007	coordination (finger tapping with-/without vision of each other's action)	EEG	1. A marked depression in occipital alpha and rolandic mu rhythms during social interaction was revealed, regardless of coordination 2. A pair of oscillatory components (phi1 and phi2) located right centroparietal cortex distinguished effective from ineffective coordination: increase of phi1 favored independent behavior and increase of phi2 favored coordinated behavior 3. The topography of the phi complex is consistent with neuroanatomical sources within the human mirror neuron system
Yun, Kyongsik et al. [117]	2012	coordination (fingertip movement)	EEG	The increase of interpersonal body movement synchrony via interpersonal interaction can be a measurable basis of implicit social interaction.

Konvalinka, Ivana et al. [118]	2014	coordination (finger-tapping task , a computer metronome)	EEG	The spontaneous emergence of leaderfollower relationships in dyadic interactions can be predicted from EEG recordings of brain activity prior to and during interaction.
Novembre, Giacomo et al. [119]	2017	coordination (joint finger-tapping task)	EEG	Phase-coupling of beta band neural oscillations across two individuals (resting) motor cortices supports the interpersonal alignment of sensorimotor processes that regulate rhythmic action initiation
Miles, Lynden K. et al. [120]	2011	coordination (performing rhythmic action)	EEG	Stable coordination (i.e., in-phase synchrony) was most pronounced when participants interacted with a member of a different minimal group
Goldstein, Pavel et al. [121]	2018	coordination (seat back to back measuring brainwave under pain–no-pain and touch–no-touch conditions)	EEG	Hand-holding during pain administration increases brain-to-brain coupling in a network that mainly involves the central regions of the pain target and the right hemisphere of the pain observer.
Poulsen et al. [122]	2017	coordination (video presentation)	EEG	1. The neural reliability, as quantified by ISC, has been linked to engagement and attentional modulation in earlier studies that used high-grade equipment in laboratory settings 2. stimulus-evoked neural responses, known to be modulated by attention, can be tracked for groups of students with synchronized EEG acquisition

Nummenmaa, L. et al. [123]	2012	coordination (video stimulus)	fMRI	1. Negative valence synchronizes individuals' brain areas supporting emotional sensations and understanding of another's actions, whereas high arousal directs individuals' attention to similar features of the environment 2. By enhancing the synchrony of brain activity across individuals, emotions may promote social interaction and facilitate interpersonal understanding
Hasson, U. [124]	2004	coordination (video watching)	Functional neuroimaging	A striking level of voxel-by-voxel synchronization between individuals was founded, not only in primary and secondary visual and auditory areas but also in association cortices
Mu, Yan et al. [125]	2016	coordination (coordination game)	EEG	Oxytocin enhances inter-brain synchrony in male adults to facilitate social coordination.
Zhou, Guangyu et al. [126]	2015	coordination (hand-opening and hand-closing movement)	MEG + accelerometer	The beta-modulation in the early visual cortices depends on the subject's role as a follower or leader in a joint hand-action task
Liu, Ning et al. [42]	2015	cooperation (Jenga game in different conditions(cooperation, parallel play, obstructive interaction))	fNIRS	1. Strong INS was observed in the posterior region of the right middle and superior frontal gyrus, in particular Brodmann area 8 (BA8), during cooperative and obstructive interaction 2. INS was also observed in the dorsomedial prefrontal cortex (dmPFC), in particular Brodmann 9, during cooperative interaction only

Pan, Yafeng et al. [68]	2017	cooperation (feedback returned key-pressing game (not face by face))	fNIRS	1. Lover dyads demonstrated increased INS in right superior frontal cortex, which also covaried with their task performance. 2. Stronger directional synchronization from females to males than from males to females was revealed
Dommer, Lukas et al. [74]	2012	Economic game (n-back task; 2pn with time lag)	fNIR	1. Between-brain coherence significantly increased during joint task performance. 2. Averaged hemodynamic responses revealed larger responses in total hemoglobin concentration changes [tHb] for the paired players as compared to the single players
Shaw, Daniel J. et al. [127]	2018	Economic games (a modified iterated Ultimatum Game (iUG))	fMRI	Brain signals implicated in social decision making are modulated by these estimates of expected utility(EU), and become correlated more strongly between interacting players who reciprocate one another.
Krueger, F. et al. [128]	2007	Economic games (strangers in trust games)	fMRI	The paracingulate cortex is critically involved in building a trust relationship by inferring another persons intentions to predict subsequent behavior.
De Vico Fallani, Fabrizio et al. [129]	2010	Economic games(Prisoner's Dilemma)	EEG	1. The hyper-brain networks of two defector couples have significantly less inter-brain links and overall higher modularityi.e., the tendency to form two separate subgraphsthan couples playing cooperative or tit-for-tat strategies. 2.The decision to defect can be "read" in advance by evaluating the changes of connectivity pattern in the hyper-brain network

Stone, Bradly et al. [130]	2015	Economic games (video game Tetris)	EEG	1.The intra-individual preliminary results presented herein indicate significant elevation in fronto-parietal coherence 2. the low-skilled players experienced an increase in Theta coherence and high Alpha coherence 2. The high-skilled players had significant reductions in fronto-parietal high Alpha coherence and small increases in Theta. 3. The inter-individual (coach-learner) dyadic coherence results for the low-skilled player showed increased Theta coherence for Coach-Frontal: Learner-Parietal (CF:LP), with no significant change in high Alpha. 4. an increase in high Alpha coherence was observed in the Coach-Parietal: Learner-Frontal (CP:LF). The high-skilled player experienced decreased Theta coherence for CF:LP, with no significant change in high Alpha 5. Yet a substantial increase in Theta coherence and decrease in high Alpha coherence was observed for CP:LF.
Tang, Honghong et al. [43]	2016	Economic games(an adapted ultimatum game)	fNIRS	Increased interpersonal brain synchronizations was founded during face-to-face interactions in right temporo-parietal junction (rTPJ) (but not in right dorso-lateral prefrontal cortex (rDLPFC)) with greater shared intentionality between partners
Jahng, Jae-hwan et al. [131]	2017	Economic games(Prisoner's Dilemma Game)	EEG	The power of the alpha frequency band (813 Hz) in the right temporoparietal region immediately after seeing a round outcome significantly differed between face-to-face and face-blocked conditions and predicted whether an individual would adopt a 'cooperation' or 'defection' strategy

Hirsch, Joy et al. [67]	2017	Eye contact/gaze tasks (gaze movement VS face picture watching)	fNIRS	Cross-brain coherence during eye-to-eye contact relative to eye-to-picture gaze increased for signals originating within left superior temporal, middle temporal, and supramarginal gyri as well as the pre- and supplementary motor cortices of both interacting brains.
Leong, Victoria et al. [132]	2017	Eye contact/gaze tasks (infants video watching in different gaze setting)	EEG	1. Direct gaze strengthens bidirectional adultinfant neural connectivity during communication. 2. Ostensive social signals could act to bring brains into mutual temporal alignment, creating a joint-networked state that is structured to facilitate information transfer during early communication and learning.
Koike, Takahiko et al. [133]	2015	Eye contact/gaze tasks and cooperation (mutual gaze task + joint attention task)	fMRI + eye tracking	1. The joint attention task enhanced eye-blink synchronization, which is believed to be a behavioral index of shared attention 2. The right inferior frontal gyrus had been activated both by initiating and responding to joint attention 2. Shared attention is represented and retained by pair-specific neural synchronization that cannot be reduced to the individual level
Fairhurst, Merle T. et al. [134]	2013	imitation (one participants with virtual partner and auditory pacing signal)	fMRI	Leading are correlated with right lateralized frontal activation of areas involved in cognitive control and self-related processing

Dumas, Guillaume et al. [135]	2010	Imitation task (hand-movement imitation)	EEG	States of interactional synchrony correlate with the emergence of an interbrain synchronization network in the alpha-mu band between the right centroparietal regions
Holper, Lisa et al. [136]	2012	imitation task(finger tapping imitation)	fNIRS	fNIRS is a suitable tool for evaluating between-brain connectivity during dynamic interaction between two persons and that those measurements might be able to provide additional insight into activation patterns not detectable using typical single-person experiments
Toppi, Jlenia et al. [137]	2016	Natural scenario (pilot cruise task)	EEG	Interbrain connectivity was, in fact, more informative in the investigation of cooperative behavior with respect to established EEG signal processing methodologies applied at a single subject level.
Dikker, Suzanne et al. [138]	2017	Natural scenario (student class recording)	EEG	Brain-to-brain synchrony is a possible neural marker for dynamic social interactions, likely driven by shared attention mechanisms.
Kawasaki, Masahiro et al. [139]	2013	speech (speech face-to-face)	EEG	1. Inter-brain synchronizations are tightly linked to speech synchronizations between subjects 2. Inter-brain synchronization might reflect empathy for others speech rhythms.
Baess, Pamela et al. [140]	2012	speech (communication with phone)	MEG	MEG-to-MEG setup, with its high temporal resolution and reasonable spatial resolution, therefore, provides a promising tool for studying the brain basis of social interaction

Stolk, Arjen et al. [141]	2014	speech (games with geometrical tokens by communicating)	fMRI	1.Cerebral dynamics synchronizes across communicators right temporal lobes 2. Interpersonal cerebral coherence occurred only within pairs with a shared communicative history, and at temporal scales independent from signals occurrences.
Spiegelhalder, Kai et al. [142]	2013	speech (live verbal interaction)	fMRI	Time course of neural activity in areas associated with speech production was coupled with the time course of neural activity in the interlocutors auditory cortex
Dai, Bohan et al. [143]	2018	speech (conversation)	FNIRS	1. Selectively enhanced INS between the listener and the attended speaker at left temporalparietal junction was founded 2. INS increases significantly prior to the occurrence of verbal responses. 3. The INS increase is independent of brain to-speech synchronization in both the anatomical location and frequency range.
Jiang, J. et al. [144]	2012	speech (face-to-face communication)	fNIRS	1. A significant increase in the neural synchronization in the left inferior frontal cortex during a face-to-face dialog between partners but none during a back-to-back dialog, a face-to-face monologue, or a back-to-back monologue was founded . 2. Neural synchronization between partners during the face-to-face dialog resulted primarily from the direct interactions between the partners, including multimodal sensory information integration and turn-taking behavior
Ahn, Sangtae et al. [145]	2017	speech(verbal interaction)	EEG / MEG	Significant oscillations in EEG alpha and MEG alpha/ gamma bands in several brain regions for all subjects was founded

Prez, Alejandro et al. [146]	2017	speech(listener and speaker)	EEG	1. Brain oscillations are synchronized between listener and speaker during oral narratives 2. Verbal information exchange cannot be fully understood by examining the listener's or speaker's brain activity in isolation.

EEG electrode positions in this experiment is shown in Fig.A.44. The corresponding brain areas of electrodes are listed in Tab.A.8 [147] [148].

A.7 Brain Areas of the Corresponding EEG Electrodes

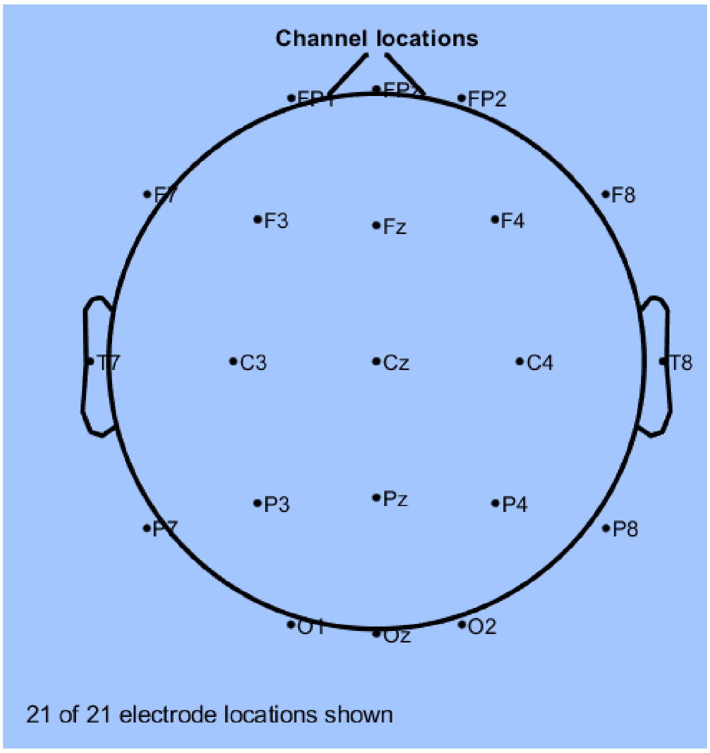

Figure A.44: Electrodes position in this paper.

electrode labels	Gyri	BA	Function name	Function
FP1	Superior frontal Gyri	10	Frontopolar (DLFC)	it is involved in strategic processes in memory recall and various executive functions.
FPz	Bilat,medial	10		
FP2	Superioro forntal Gyri	10		
F7	Inferior frontal Gyri	45	Triangular	It is active in semantic tasks, such as semantic decision tasks (determining whether a word represents an abstract or a concrete entity) and generation tasks (generating a verb associated with a noun).
F3	Middle frontal Gyri	8		It is involved in planning complex movements.

Fz	Bilat,medial	6	Premotor cortex and Supplementary Motor Cortex	It is believed to play a role in the planning of complex, coordinated movements.
F4	Middle frontal Gyri	8		It is involved in planning complex movements.
F8	Inferior frontal Gyri	45	Triangular	It is active in semantic tasks, such as semantic decision tasks (determining whether a word represents an abstract or a concrete entity) and generation tasks (generating a verb associated with a noun).
T7	Middle temporal Gyri	21		It plays a part in auditory processing and language.
C3	Postcentral Gyri	123	Primary Somatosensory Cortex	It is the main sensory receptive area for the sense of touch.
Cz	Precentral Gyri	4	Primary Motor Cortex	It works in association with other motor areas to plan and execute movements
C4	Postcentral Gyri	123	Primary Somatosensory Cortex	It is the main sensory receptive area for the sense of touch.
T8	Middle temporal Gyri	21		It plays a part in auditory processing and language.
P7	Inferior temporal Gyri	37	Occipitotemporal	BA37 is involved in lexico-semantic associations (i.e., associated words with visual percepts).
P3	Precuneus	19	Peristriate (Tertiary or Associative visual cortex, V3)	It is a visual association area, with feature-extracting, shape recognition, attentional, and multimodal integrating functions.
Pz	Superior parietal L	7	Somatosensory Association Cortex	It is involved in locating objects in space.
P4	Inferior parietal L	7	Somatosensory Association Cortex	It is involved in locating objects in space.
P8	Inferior temporal Gyri	19	Peristriate (Tertiary or Associative visual cortex, V3)	It is a visual association area, with feature-extracting, shape recognition, attentional, and multimodal integrating functions.

O1	Middle occipital Gyri	18	Parastriate (Secondary visual cortex, V2)	It is known as a ”Visual Association Area” and is responsible for the interpretation of images.
Oz	Ceneus	18		
O2	Middle occipital Gyri	18		

A.8 Experimental data Software Package

A.8.1 Software Packages

Software packages applied in this paper include:

- EEGLab
- BCT: Brain Connectivity Toolbox. The website is `https://sites.google.com/site/bctnet/`
- Easy Plot EEG Brain Network Matlab. A matlab file toolbox for plot brain networks. Please check this webpage.
- SmallWorldNess. Matlab toolbox for calculating small-world-ness. Please check this webpage.

A.8.2 Experimental Data and Code

9 dyads attended this pong-game experiment. Screen-videos of all these sessions are shared on Good drive.

For the first 6 dyads, there are 4 sessions for competition and cooperation. For the last 3 dyads, there are 2 sessions for competition and cooperation. The data is shared on Google drive. The matlab code is shared on this link. Please read step.txt (which details the workflow) first.