COMPLEX SYSTEMS – Portfolio

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ENTRY No.1

Module 7

Research Question : Analysing short-range phase synchronization in the brain during music perception and Imagination using the "Open Miir" EEG dataset(1).

Description of the dataset

The dataset used for this portfolio was recorded for the Open Miir project. During this experiment, the participants listen to musical pieces of various genre and presenting different rhythmic features. For each piece, the participants were first asked to listen to it. This part of the recording is referred to as "perception". Then, participants engaged in three types of music imagination tasks : one with rhythmic cues preceding imagination and two without any cues (with feedback from the participant regarding self-evaluation of imagination performances or not).

Method

Before being able to conduct relevant assessment of synchrony, we need to remove eye blinks and heart beats artifacts from the Raw EEG data. This is done using the find_bads_eog and find_bads_ec g functions from the MNE python package. Since the dataset doesn't features an EOG nor an ECG channel, we use the FP1 channel as a virtual channel. After having excluded these artifacts from the ICA components, we can reconstruct the pre-processed EEG dataset.

For the following analysis, we select two epochs from one participant that corresponds to the imagination and perception tasks based on the same piece. The dataset features 68 channels, but for this project, we will focus on computing short-range measures of synchrony. Therefore, we use the pick function to select channels from only the left-hemisphere the brain. In order to be able to measure inter-lobes synchrony, we select 3 channels from 3 adjacent lobe :

- Channels C1, C3 and C5 for the Parietal lobe.

- Channels F1 and F3 for the Frontal lobe.

- Channels T7, FT7 and TP7 for the Temporal lobe.

Synchrony will be compared across tasks.

To do so, for each piece we compute the RQA RR and CRQA RR measures of recurrence probability.

Since our data shows complex dynamics and features continuous variables, we need to estimate the embedding parameters beforehand : the embedding dimension with false-nearest-neighbor function and time delay with the the average mutual information function.

The following table present the obtained embedding parameters :

	PERCEPTION		IMAGINATION	
	Delay	**Embedding Dimension**	**Delay**	**Embedding Dimension**
C1	12	4	4	2
C3	5	6	6	3
C5	4	6	6	3
F1	4	5	4	2
F3	5	5	4	2
T7	5	5	5	5
FT7	5	5	4	5
TP7	5	5	4	2

For the CRQA computation, we average the embedding and delay values of each pair of channel.

This analysis provides a Recurrence Rate measure and allows to compare the inter-lobes synchrony. From the multiple CRQA computed between each pair of channel of the 3 lobes , we extract averages of CRQA between each pair of lobes (Frontal-Parietal, Temporal-Frontal, Temporal Parietal).

Results

After running RQA and CRQA for each channels and pair of channels respectively, we obtain the following tables :

Channel Name	RR RQA -Pe	RR RQA Im
C1	0.79	0.99
C3	0.95	0.92
C5	0.97	0.93
F1	0.78	0.87
T7	0.85	0.98
FT7	0.97	0.86
TP7	0.96	0.93

	RR CRQA
PeCT	0.98
PeFT	0.97
PeCF	0.98
ICT	0.99
IFT	0.95
ICF	0.99

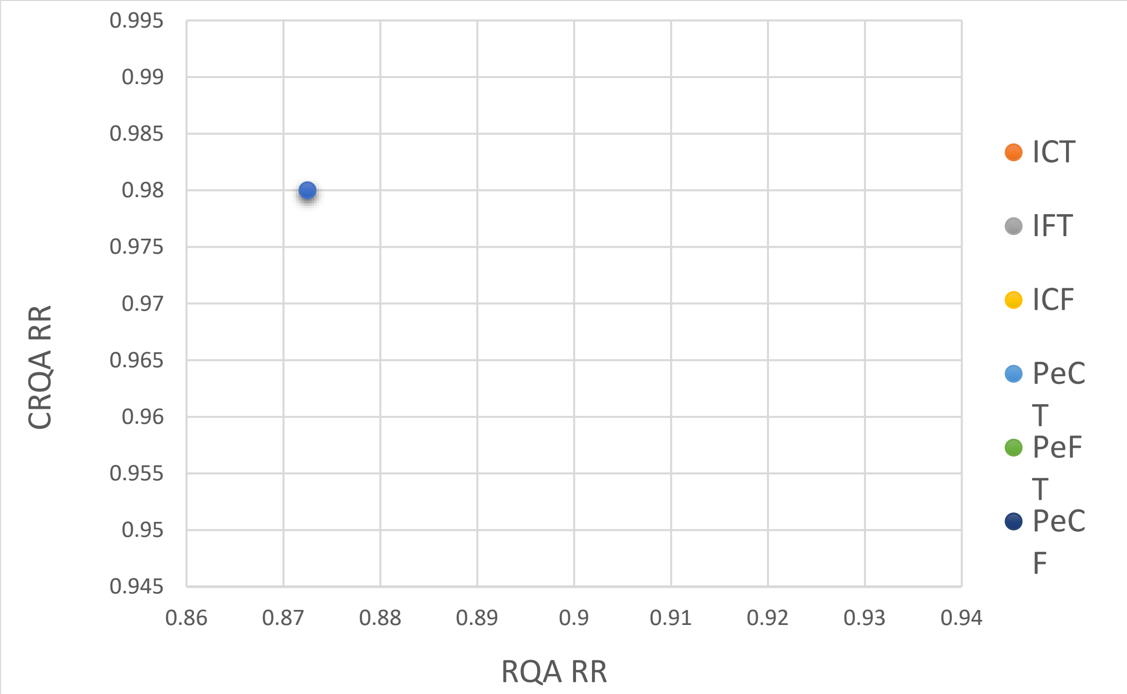

Fig 2 . Feature space of average RQA RR and average CRQA RR for : Perception Parietal-Temporal synchrony (PeCT), Perception Frontal-Temporal synchrony (PeFT), Perception Parietal-Frontal synchrony (PeCF), Imagination Parietal-Temporal synchrony (ICT), Imagination Frontal -Temporal synchrony (IFT) and Imagination Parietal-Frontal synchrony (ICF).

The results show excessively high recurrence rates over the conducted RQA and CRQA analysis. This might suggest that the dataset features overly periodic dynamics. However, RQA and CRQA has been conducted on EEG data multiple times and did not revealed such periodicity (1,2). It is not reasonable to assume that this is an intrinsic property of the brain activity associated with musical perception nor imagination processes. Therefore, these results certainly seems to reflect very noisy data and incomplete artifact rejection.

References :

(1) Stober, S. et al. “Towards Music Imagery Information Retrieval: Introducing the OpenMIIR Dataset of EEG Recordings from Music Perception and Imagination.” ISMIR (2015).

(2) Bhattacharya, J. and H. Petsche. “Phase synchrony analysis of EEG during music perception reveals changes in functional connectivity due to musical expertise.” Signal Process. 85 (2005): 2161-2177.

(3) L. T. Timothy, B. M. Krishna and U. Nair, "Combined recurrence and cross recurrence quantification of MCI EEG," 2015 International Conference on Power, Instrumentation, Control and Computing (PICC), 2015, pp. 1-5, doi: 10.1109/PICC.2015.7455807.

ENTRY No 2

Module 8

Research Question : How well can EEG Data recorded during musical perception and imagination be predicted based on information provided across different lobes ? Are auditory stimulus necessary to stabilize the complex dynamics of this system ?

Following the analysis conducted in the first entry of this portfolio, it seems relevant to investigate the relation between the complex dynamics measured across tasks and brain regions and the predictive performances that can be achieved based on these connected networks. In this project, we will compare the performances of univariate and multiples Multivariate embedding Empirical Dynamic Modelling. In the first type of model, since we expect the EEG data recorded by channels within the same lobe to be the most related, we use every channel from each lobe for multivariate embedding. In the second type of model, we only use channels from another lobe for multivariate embedding. The forecast skill is then compared across lobes and imagination or perception tasks. As we want to maximize the synchrony that it is possible to observe between brain activity captured by each channel, we decide to only select channels from the left hemisphere. In our analysis, the Temporal lobe activity is reflected by T7, Frontal by F1 and Parietal by C1,C3 and C5.

Since we assume that synchrony properties found in the previous entry are emerging from phase locked brain activity in response to auditory stimulus, we should expect that the forecast skill will decay faster when the subject is performing a “musical imagination” task compared to a “musical imagination” task (2). In order to make the distinction between these two tasks as meaningful as possible, we decide to only keep data from trials without rhythmic cues for the “imagination” condition.

Method

In order to assess the if the predictive abilities of our models decays over time, we define multiple sets of points, each further away from the information used to reconstruct the state space. Then, we compare the forecast skill score achieved over time. Each trial is reduced to 4.5 secondes (approximated to 2000 data points). In order to be able to build 4 distinct set of points to predict form a single state space reconstruction, the library set is kept to a fifth of the total amount of data used. Each of the sets used for prediction takes a fourth of the remaining data points.

	Forecast skill				**Multivariate**	
Channel Name	**Set 1 (500-1000)**	**Set 2 (1000-1500)**	**Set 3 (500-1000)**	**Set 4 (500-1000)**	Intra-lobes	Inter-lobes
C1	0.7393449	0.5746635	0.43653	0.51951	0.5932	0.438462
C3	0.8692395	0.833293	0.8182644	0.8966022		
C5	0.4981813	0.74306	0.5404412	0.71569		
F1	0.6656626	0.7287974	0.6933019	0.2835131		
T7	0.78305	0.6740384	0.3945322	0.595462	0.356141	0.454397

Thus, each univariate model is ran over every of the selected channels across both conditions four times and provides us with the following tables :

Table 1 : Performances of the univariate and multivariate models over distanced prediction sets for channels across the Frontal (F1), Temporal (T7) and parietal (C1,C3 and C5) - Perception Task.

	Forecast skill			
Channel Name	**Set 1 (500-1000)**	**Set 2 (1000-1500)**	**Set 3 (500-1000)**	**Set 4 (500-1000)**
C1	0.7393449	0.5746635	0.43653	0.51951
C3	0.8692395	0.833293	0.8182644	0.8966022
C5	0.4981813	0.74306	0.5404412	0.71569
F1	0.6656626	0.7287974	0.6933019	0.2835131
T7	0.78305	0.6740384	0.3945322	0.595462

Table 2 : Performances of the univariate model over distanced prediction sets for channels across the Frontal (F1), Temporal (T7) and parietal (C1,C3 and C5) - Imagination Task (without cues).

Results

The evolution of the univariate model performances doesn't show a clear trend. In the Imagination condition, the forecast skill rises by 3% on average when the prediction set is shifted from set 1 to 2. In drop by almost 17% from set 1 to set 3 and by about 13% from set 1 to set 4.

In the perception condition, if we exclude the first channel for which we observe extreme variations between set 1 and 2, the forecast skill drops by 7.8%, then by 12% between set 1 to 3 and 20% on average between set 1 to 4.

But since the forecast skill measure features very high variance across channels and conditions, we can't conclude on intrinsic differences between the brain activity associated with perception and imagination in terms of predictability and stability of the complex dynamics (3). However, the trend that appears from these results is unexpected regarding our initial hypothesis. Further research based on more advanced artifact rejection methods is needed to confirm these findings.

References :

(1) Stober, S. et al. "Towards Music Imagery Information Retrieval: Introducing the OpenMIIR Dataset of EEG Recordings from Music Perception and Imagination." ISMIR (2015).

(2)Shahin AJ, Trainor LJ, Roberts LE, Backer KC, Miller LM. Development of auditory phase-locked activity for music sounds. J Neurophysiol. 2010 Jan;103(1):218-29. doi: 10.1152/jn.00402.2009. Epub 2009 Oct 28. PMID: 19864443; PMCID: PMC2807221.

(3) Bhattacharya, J. and H. Petsche. "Phase synchrony analysis of EEG during music perception reveals changes in functional connectivity due to musical expertise." Signal Process. 85 (2005): 2161-2177.