

Neuroengineering 2021-2022  
**Exam 23 June 2022 – Part II**  
**(odd seats)**

## **Solutions**

- A1.** Indicate **which technique** for the **acquisition** of **neuroelectrical signals** you would use, and **why**. List the pros and cons of your choice. (*2 points*)

The text specifies that the regions to be included in the analysis are cortical ones. This, together with the fact that the subjects enrolled are healthy volunteers, suggests that scalp EEG is the best option for the recordings.

Pros: scalp EEG is non-invasive, inexpensive, easy to use, and portable, it has the same (excellent) temporal resolution as invasive methods, and allows face-to-face interaction between the subjects.

Cons: spatial blur (attenuation and spread of the potential with distance), low signal-to-noise ratio, multiple sources contribute to the single electrode signal and, conversely, near electrodes record partially overlapped (correlated) signals. However, all these limitations are stronger for deeper regions, while here we are only interested in cortical ones.

- A2.** Indicate **which connectivity estimator** you would use to perform the **network analysis**. Justify your choice and indicate the related pros and cons. (*3 points*)

The text indicates that we are interested in an analysis of causality. This restricts the choice to the Granger Test or the Partial Directed Coherence (in fact, the other estimator, the Ordinary Coherence, is not a measure of causality). Since it is specified that, to prevent habituation and learning, we have short data recordings, we can infer that the amount of data available is not sufficient to compute PDC, which requires long data segments or many trials due to the number of parameters to be estimated for the multivariate model. Therefore, the Granger Test is the best option.

Pros: it is a measure of causality, and it doesn't require long recordings.

Cons: it is bivariate (problem of the hidden source, that can result in a reduced accuracy), it is not a spectral measure.

- A3.** Given the multi-subject functional connectivity network obtained, made of 8 regions, as reported in **Fig.1:**

**A3.1.** Extract the corresponding **adjacency matrix** (*0.5 points*)

**A3.2.** Compute the **in-degree** and **out-degree** of each node (*0.5 points*)

		Out-degree									
		3	2	3	2	1	0	1	1	1	
In-degree	2	0	1	0	1	0	0	0	0	0	1
	0	0	0	0	0	0	0	0	0	0	1
	0	0	0	0	0	0	0	0	0	0	1
	1	0	0	1	0	0	0	0	0	0	1
	2	0	0	1	1	0	0	0	0	0	2
	4	1	0	1	0	1	0	1	0	0	2
	3	1	1	0	0	0	0	0	0	1	2
	1	1	0	0	0	0	0	0	0	0	2
		1	1	1	1	2	2	2	2	2	

- A3.3.** Compute the **Divisibility D** and the **Modularity Q** of the network, considering the two subjects as classes:  $C_a = [1,1,1,1,2,2,2,2]$  (*2 points*)

		Out-degree									
		3	2	3	2	1	0	1	1	1	
In-degree	2	0	1	0	1	0	0	0	0	0	1
	0	0	0	0	0	0	0	0	0	0	1
	0	0	0	0	0	0	0	0	0	0	1
	1	0	0	1	0	0	0	0	0	0	1
	2	0	0	1	1	0	0	0	0	0	2
	4	1	0	1	0	1	0	1	0	0	2
	3	1	1	0	0	0	0	0	0	1	2
	1	1	0	0	0	0	0	0	0	0	2
		1	1	1	1	2	2	2	2	2	

$$\begin{aligned} N &= 8 \\ L &= 13 \\ C_a &= [1,1,1,1,2,2,2,2] \end{aligned}$$

$$D = \frac{L}{L + \sum_{i,j=1}^N a_{ij} [1 - \delta(C_i, C_j)]} = \frac{13}{13 + 0 + 7} = 0.65$$

$$\begin{aligned} Q &= \frac{1}{L} \sum_{i,j=1}^N (a_{ij} - \frac{g_i^{OUT} g_j^{IN}}{L}) \delta(C_i, C_j) = \\ &= \frac{1}{13} \left[ 3 - \frac{(g_1^{OUT} + g_2^{OUT} + g_3^{OUT} + g_4^{OUT})(g_1^{IN} + g_2^{IN} + g_3^{IN} + g_4^{IN})}{13} + 3 - \frac{(g_5^{OUT} + g_6^{OUT})(g_5^{IN} + g_6^{IN})}{13} \right] = \\ &= \frac{1}{13} \left[ 3 - \frac{(3+2+3+2)(2+0+0+1)}{13} + 3 - \frac{(1+0+1+1)(2+4+3+1)}{13} \right] = \frac{1}{13} [3 - 2.31 + 3 - 2.31] = 0.11 \end{aligned}$$

**A3.4.** Compute the **Divisibility D** and the **Modularity Q** of the network, considering two groups of homologous regions belonging to **both** subjects as classes:  $C_b=[1,1,2,2,2,1,1]$  (2 points)

		Out-degree									
		3	2	3	2	1	0	1	1		
In-degree	2	0	1	0	1	0	0	0	0	1	
	0	0	0	0	0	0	0	0	0	1	
	0	0	0	0	0	0	0	0	0	2	
	1	0	0	1	0	0	0	0	0	2	
	2	0	0	1	1	0	0	0	0	2	
	4	1	0	1	0	1	0	1	0	2	
	3	1	1	0	0	0	0	0	1	1	
	1	1	0	0	0	0	0	0	0	1	
		1	1	2	2	2	2	1	1		

$$\begin{aligned} N &= 8 \\ L &= 13 \\ C_a &= [1,1,1,1,2,2,2,2] \end{aligned}$$

$$D = \frac{L}{L + \sum_{i,j=1}^N a_{ij}[1 - \delta(C_i, C_j)]} = \frac{13}{13 + 1 + 2} = 0.82$$

$$\begin{aligned} Q &= \frac{1}{L} \sum_{i,j=1}^N (a_{ij} - \frac{g_i^{OUT} g_j^{IN}}{L}) \delta(C_i, C_j) = \\ &= \frac{1}{13} \left[ 5 - \frac{(g_1^{OUT} + g_2^{OUT} + g_3^{OUT} + g_4^{OUT})(g_1^{IN} + g_2^{IN} + g_3^{IN} + g_4^{IN})}{13} + 5 - \frac{(g_5^{OUT} + g_6^{OUT})(g_5^{IN} + g_6^{IN})}{13} \right] = \\ &= \frac{1}{13} \left[ 5 - \frac{(3+2+1+1)(2+0+3+1)}{13} + 5 - \frac{(3+2+1+0)(0+1+2+4)}{13} \right] = \frac{1}{13} [5 - 3.23 + 5 - 3.23] = 0.27 \end{aligned}$$

**A4.** Comment on the results obtained at point A3. According to D and Q computed for the two divisions in classes  $C_a$  and  $C_b$ , are the two subjects' brains working independently, or do they influence each other during the collaboration task? (1 point)

In the first division in classes ( $C_a$ ), areas belonging to different brains are assigned to different classes.

In the second division ( $C_b$ ), homologous areas belonging to different brains are assigned to the same class.

Therefore, the level of segregation according to  $C_a$  will be inversely proportional to the interdependency between the two subjects' brains, while the level of segregation according to  $C_b$  will be directly proportional to the interdependency between the brains.

Since D and Q are higher for  $C_b$  with respect to  $C_a$ , we can conclude that the two subjects' brains influence each other during the collaboration task.