PhD thesis: **Development of Network Features for Brain-Computer Interfaces**
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1 Context

A **Brain-Computer Interface** (**BCI**) is a system that can translate brain activity patterns into messages or commands for an interactive application (Lotte, Bougrain, and Clerc, 2015). It enables a subject to send commands to a device only by means of brain activity, without requiring any peripherical muscular activity. These systems are increasingly explored for control and communication, as well as for treatment of neurological disorders, especially via the ability of subjects to voluntarily modulate their brain activity through mental imagery (Pfurtscheller and Da Silva, 1999).

To control a BCI, the user must produce different brain signal patterns that the system will identify and translate into commands. Even though this technique has been widely used, subjects' performance, measured as the correct classification of the user's intent, still shows low scores. Much of the efforts to solve this problem have focused on the BCI classification block (Lotte et al., 2018), while the research of alternative features has been poorly explored. In most implemented systems, pattern recognition relies on power spectrum density (PSD) of a reduced number of sources, focusing on features that characterize a single brain region.

However, the brain is not a collection of isolated pieces working independently. It rather consists of a distributed complex network that integrates information across differently specialized regions. It turns out that examining signals from one specific region, while neglecting its interactions with others, oversimplifies the phenomenon. It would be preferable to have an understanding of the system's collective behavior to fully capture the brain functioning. Thus, we think that **functional connectivity** (**FC**) features could be more representative of the complexity of neurophysiological processes, since it measures interactions between different brain areas, reflecting the information exchange that is essential to decode brain organization (Bastos and Schoffelen, 2016; Cattai et al., 2021). Then, these interactions can be synthesized using network theory estimators, modeling the human brain as a network. Certainly, network analysis may exhibit a more accurate performance since it optimizes computational cost and dimensionality (Gonzalez-Astudillo et al., 2021).

Nevertheless, just extracting topological properties of the network, disregarding the intrinsic spatial nature of the brain, might be missing crucial information for understanding brain functioning. Recent neuroimaging studies demonstrated that brain connectivity reveals hemisphere lateralization during motor-related tasks (Cattai et al., 2021). Covering these two concepts, in this project we explored the dual contribution of brain network topology and space in modelling motor mental states through functional lateralization.

2 State-of-the-art

One of the most studied paradigms in BCI is **motor imagery** (**MI**), due to its wide range of applications such as controlling devices, virtual reality, or even neurorehabilitation (Lotte, Bougrain, and Clerc, 2015). MI is defined as the conscious cognitive process of having the intention of a movement without actually performing it (Jeannerod, 1995; Lotze and Halsband, 2006). MI-based BCI relies on the imagination of kinesthetic movement of large body parts such as hands, feet, and tongue (Guillot et al., 2009). This results in modulations of brain activity associated with event-related desynchronization (ERD) in α (8-13 Hz) and β rhythms (18-30 Hz). By contrast, resting state results in event-related synchronization (ERS).

Identifying mental intentions from brain signals requires working in different domains, temporal, frequency, and space. Since EEG, as many other neuroimaging techniques, are often characterized by noisy measurements and low spatial resolution it is necessary to implement methods that enhance characteristics that define each mental task. In the particular case of MI, ERD and ERS modulations are most prominent in signals acquired from electrodes located above the sensorimotor cortex (Pfurtscheller and Aranibar, 1977; Pfurtscheller and Neuper, 1997; Neuper, 1999). Then one smart solution is to apply spatial filtering. These methods try to collect this information while reducing the influence of the surrounding activity. In the last decades, the most reproduced in the BCIs fields is **Common Spatial Patterns** (**CSP**) (Ramoser, Muller-gerking, and Pfurtscheller, 1999; Pfurtscheller and Neuper, 2001; Blankertz et al., 2005; Blankertz et al., 2007). This filter works as a data-driven dimension reduction method that aims to extract the signal sources by maximizing the variance ratio between two conditions (e.g. MI versus resting). It is based on the simultaneous diagonalization of two covariance matrices of the band-pass filtered signal for the two classes. In this way, covariance matrices are just handled in the Euclidean space.

Another technique that has gained large space in the field is **Riemannian geometry** (**RG**). Basically, it enables direct manipulation of the signal covariance matrices and subspaces (Yger, Berar, and Lotte, 2016; Congedo, Barachant, and Bhatia, 2017). The core idea behind these algorithms is to work with covariance matrices in the manifold of symmetric positive-definite (SPD) matrices and use them as features in a classifier that respects their intrinsic geometry. Matrices with such property form a manifold $\mathcal{M}$, in which the tangent space at each point is a finite-dimensional Euclidean space. In particular, the approaches that use tangent space projection have been shown to out-perform most other conventional methods (Barachant et al., 2013; Jayaram and Barachant, 2018). However, these methods undergo two major disadvantages, high computational complexity and lack of interpretation. Since they work in the space of sensor covariance matrices, their size scales quadratically with the number of sensors. Then when projecting to the tangent space, this easily becomes an overfitting problem when the vector dimension is higher than the available training trials (Rodrigues et al., 2017; Congedo et al., 2017). This translates into unfeasible application in high-density BCI systems. Further, the issue of interpretation is a significant commonly forgotten problem. RG methods do not count with a direct way to determine what parts of a signal are being used to build a tangent space classifier. Neither the classifiers in the manifold contemplate for this issue (Barachant et al., 2010; Barachant et al., 2011).

3 Scientific results

Previous studies have confirmed that MI activates brain regions that are linked to actual movement generation (primary motor cortex, M1), and regions that intervene in planning and preparation of such movements (Jeannerod, 1995; Pfurtscheller and Neuper, 1997). More especially the posterior supplementary motor area (SMA) and the premotor cortex (PMA), which seem to be predominant areas. Since neurons in the SMA are involved in the preparation of movements, then it is reasonable that preparatory aspects of movement may be closely related to MI (Stephan et al., 1995). In this spatial layout of MI, another prominent characteristic is lateralization. It is well known that the motor cortex is principally involved in controlling the contralateral side of the body (Beisteiner et al., 1995).

These dynamics of brain oscillations in the motor cortex, associated with sensory, cognitive and motor processing, form complex spatial patterns reflected in changes in the FC within the implied areas. In order to explore the topology and the spatial arrangement of the resulting networks, we introduced new metrics to quantify patterns of functional brain lateralization. As starting point, we consider the qualitatively differentiation between within- and across-hemisphere interactions, that influence the strength of a region or node depending on how these contributions are conceived. Using homotopic locations in the two hemispheres, we proposed two separate properties to quantified lateralization: *segregation* (σ_{ij}) and *integration* (ω_{ij}). The first measures the tendency for greater within-hemisphere interactions compared to between-hemisphere interactions:

$$\sigma_{ij} = \frac{(LL_i + LC_i - LR_i) - (RR_j + RC_j - RL_j)}{(CL_k + CR_k + CC_k)}, \tag{1}$$

where each term represents the strength of a node in the homotopic pair of nodes i and j. In the differentiation between within- and across hemispheres edges, the capital letters respectively denotes the locations of node i and the nodes it establishes connections with (e.g. LR_i means that node i belongs to the left hemisphere and we consider the connections that link it to the right hemisphere nodes). Note that for the particular case of brain signals recorded with an EEG system, the electrodes placed in the midline sagittal plane (C_k) do not strictly belong to a hemisphere, so we consider them to normalize the metrics values.

Applying the same notation, ω_{ij} seeks the contribution of contralateral connections, characterizing how the information flows across hemispheres. Then it is defined as the summed effect of within- and across-hemispheric interactions:

$$\omega_{ij} = \frac{(LL_i + LC_i + LR_i) - (RR_j + RC_j + RL_j)}{(CL_k + CR_k + CC_k)}, \tag{2}$$

To prove the relevance of these metrics in characterizing lateralized cognitive process, we studied EEG signals from 6 different datasets of subjects performing two different task, MI of the right and left hand (Jayaram and Barachant, 2018). We estimated spectral coherence-based networks and we computed the previously described network lateralization metrics for each node or electrode. Finally, we assessed the classification performance of the introduced metrics comparing them with the state-of-the-art methods, CSP and RG, using an SVM classifier. In the results resumed in Table 1 we observed that our method gets promising accuracies but still lower than the traditional methods.

Nonetheless, we also evaluated the presence of specific task-associated patterns for each network property by statistically comparing both MI conditions. We performed a t-test at the subject level and for each node to reveal the most discriminant nodes in the differentiation between the two tasks. In the results shown in Fig. 1, we observe that both metrics engage a subset of nodes mostly located in the M1 cortex, but also the PMA, SMA and S1 areas also crucial in the planification and execution of a movement (Hétu et al., 2013). We observe that ω shows higher values, while σ also involves frontal areas, usually associated with attention and motor planning. These results show the neurophysiological plausibility of our proposed network approach. On the contrary, CSP and RG methods do not show the same precise definition when trying to decode the underlying physiology that leads their performance.

4 Scientific production

First author journal papers

1. **Gonzalez-Astudillo, J.**, Cattai, T., Bassignana, G., Corsi, M.C., and De Vico Fallani, F., 2021. "Network-based brain–computer interfaces: principles and applications". *Journal of Neural Engineering*, 18, p.011001.

2. **Gonzalez-Astudillo, J.**, and De Vico Fallani, F.. Network lateralization features for motor imagery-based brain-computer interfaces. *In Prep.*

Book chapters

1. Couvy-Duchesne, B., Bottani, S., Camenen, E., Fang, F., Fikere, M., **Gonzalez-Astudillo, J.**, Harvey, J., Hassanaly, R., Kassam, I., Lind, P. and Liu, Q., Lu, Y., Nabais, M., Rolland, T., Sidorenko, J., Strike, L., Wright, M., 2022. "Main existing datasets for open data research on humans."

Conference abstracts

1. **Gonzalez-Astudillo, J.**, Cattai, T., Corsi, M.C. and De Vico Fallani, F., 2020. "On the classification of mental states by means of network-based features." In *NetSci 2020 - Network Science Society Conference 2020.*

Talks

1. **Gonzalez-Astudillo, J.** and De Vico Fallani, F., 2022. "Spatial lateralization in motor brain networks." In *MSCx 2022: Mediterranean School of Complex Networks.*

2. **Gonzalez-Astudillo, J.** and De Vico Fallani, F., 2022. "Spatial Networks features for Brain Computer Interfaces." In *FrCCS 2022: French Regional Conference on Complex Systems.*

3. **Gonzalez-Astudillo, J.** and De Vico Fallani, F., 2022. "A spatial network alternative for BCI inefficiency." In *Journées CORTICO 2022: COllectif pour la Recherche Transdisciplinaire sur les Interfaces Cerveau-Ordinateur.*

4. **Gonzalez-Astudillo, J.**, Ceballos-Dominguez, E.G., Cattai, T., Corsi, M.C. and De Vico Fallani, F., 2021. "Spatial network metrics for characterizing brain-computer interface mental states." In *Networks 2021: A Joint Sunbelt and NetSci Conference.*

5. **Gonzalez-Astudillo, J.**, Cattai, T., Corsi, M.C. and De Vico Fallani, F., 2020. "Towards the use of spatial networks for characterizing brain mental states." In *CCS: Conference on Complex Systems - Complex-Space 2020: Analysis and Modelling of Spatial Complex Systems (Satellite).*

TABLE 1: Average accuracies across methods for each dataset.

Dataset	σ+SVM	ω+SVM	CSP+SVM	RG+SVM
001-2014	72.16 ± 15.75	74.33 ± 15.46	86.04 ± 12.05	85.31 ± 12.62
Cho2017	61.09 ± 10.24	62.95 ± 11.03	72.80 ± 13.21	75.24 ± 11.93
Lee2019MI	63.05 ± 9.63	65.63 ± 11.96	67.10 ± 16.60	76.46 ± 15.08
Schirrmeister2017	62.31 ± 9.31	66.17 ± 9.65	82.53 ± 15.43	88.16 ± 11.58
Weibo2014	62.96 ± 12.32	67.69 ± 15.64	82.75 ± 14.49	84.78 ± 13.99
Zhou2016	83.34 ± 7.81	86.52 ± 7.04	94.20 ± 5.63	94.44 ± 5.51

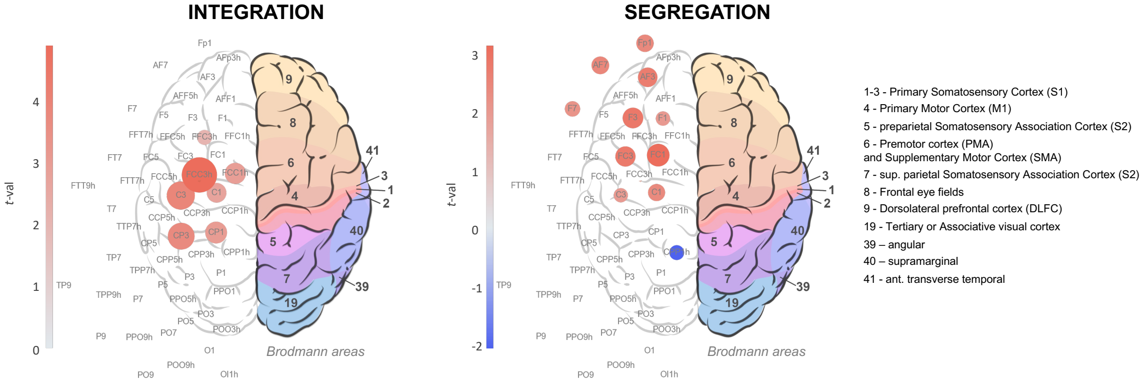

FIGURE 1: Neurophysiological interpretation of network metrics results. Group-averaged t-values, contrasting right versus left MI in the α-β band.