Multifrequency Brain Connectivity In Alzheimer's Disease: A Multilayer Network Approach

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Recent advances in network science has allowed new insights in the brain organization from a system perspective. Characterizing ***connectivity maps, estimated from neuroimaging data****, as graphs of connected nodes has not only* ***pointed out important network features*** *of the physiological brain – such as small-worldness, modularity, and regional centrality – but it has also have* ***practical applications for the development of biomarkers*** *quantifying reorganizational mechanisms of disease.*

Despite graph analysis of brain networks has advanced out understanding of neural mechanisms underlying aspects of human cognition and disease, a certain number of conceptual and technical issues still remain to be addressed. For example, ***conventional approaches analyse separately*** *spectral brain networks obtained in different frequency bands [1,2], or in some cases, they simply focus on specific frequency bands, thus* ***neglecting possible contribution*** *in other spectral contents. However, recent studies have reported that that frequency bands influence each other and can be correlated [3] while excluded frequency bands might provide additional insights on brain functioning. Here, we adopt a* ***multilayer network approach*** *to allow a* ***capture contributions and interactions between frequency-bands*** *in the brain topological profile of a single individual.*

▲ METHODS

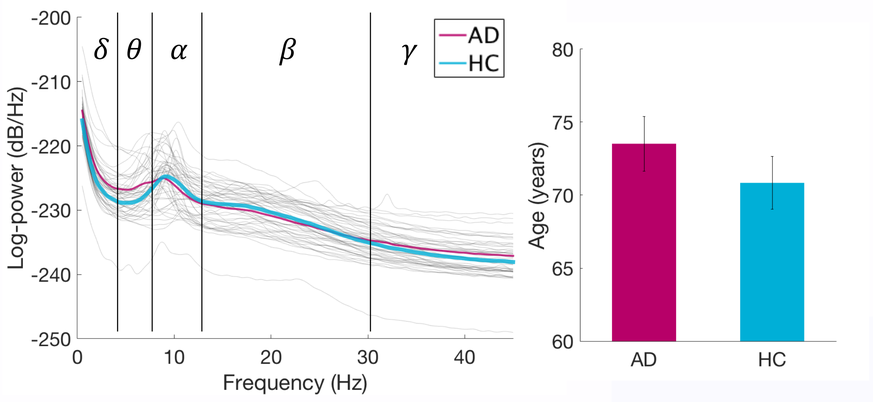

Figure 1: Subjects' mean Power Spectrum Density and age distribution between groups.

MEG recordings were obtained from 25 Alzheimer diseased (AD) patients and 25 healthy control subjects (HC) in resting state condition.

We build our multilayer networks as multiplexes which means that a node of a given layer is linked to all its counterpart in the other layers. In our case, each layer corresponds to the adjacency matrix based on the binarized imaginary coherence [4] of five frequency bands: δ (1-4 Hz), θ (4-8 Hz), α (8-13 Hz), β (13-30 Hz) and γ (30-45 Hz) as shown in **Fig. 1 and 2**.

For each methodology (the single-layer frequency band networks and the multiplex) we computed a topological measure called participation coefficient [5].

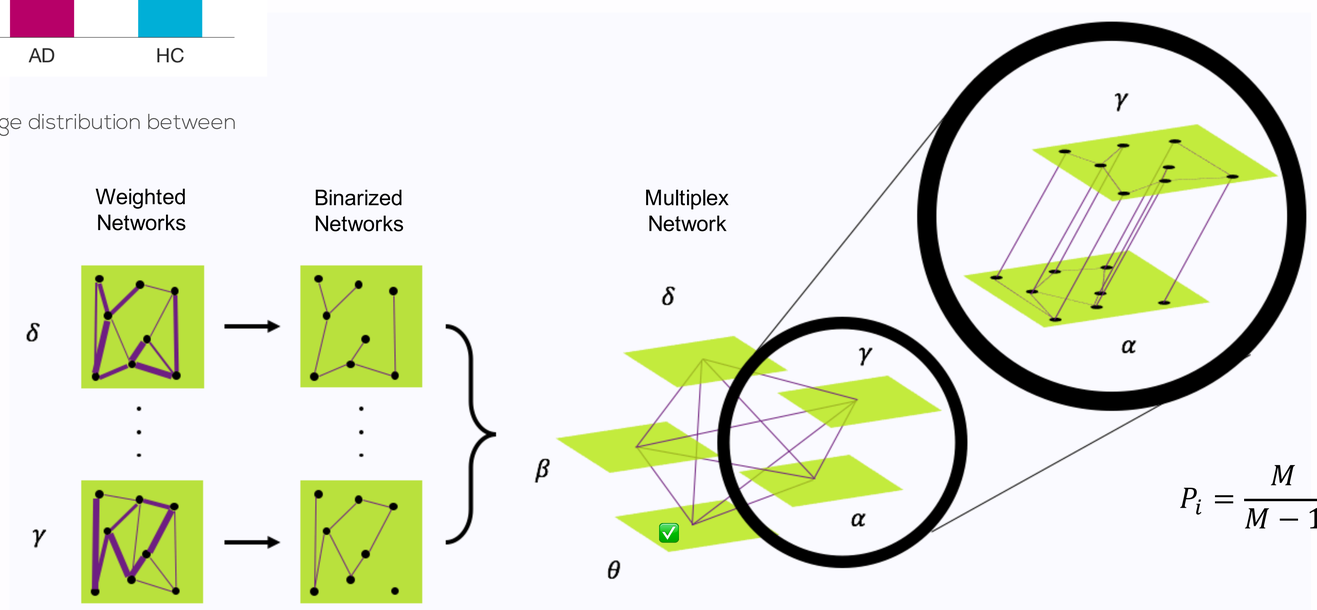

Figure 2: Multiplex construction workflow.

$$P_i = 1 - \sum_{m=1}^{N_m} \left(\frac{k_i^{[m]}}{k_i} \right)^2$$

This measure quantifies how much a node (here a brain region) interacts with different modules. In the single-layer case, modules are defined using Louvain's algorithm whereas in the multilayer case, modules correspond to layers (here different frequency bands).

$$P_i = \frac{M}{M-1} \left[1 - \sum_{\alpha=1}^{M} \left(\frac{k_i^{[\alpha]}}{o_i} \right)^2 \right]$$

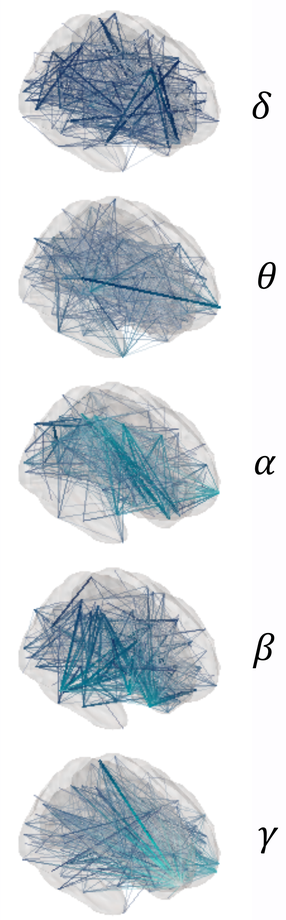

Figure 3: Brain networks visualisation example.

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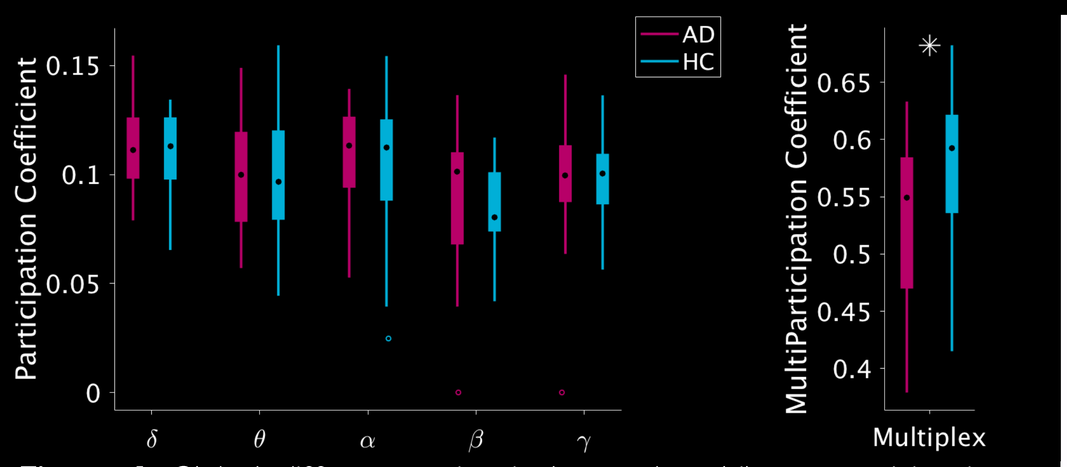

Figure 4: Global differences in single- and multilayer participation coefficient.

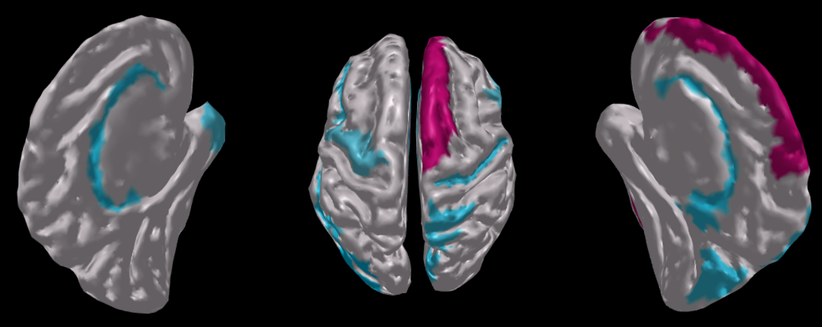

Figure 5: Local differences in multilayer participation coefficient using Destrieux atlas.

▲ RESULTS

In **Fig. 4** is presented the boxplots of the global participation coefficients (mean over the ROIs for each subject) of the two populations (AD and HC).

Results are detailed in Table 1. After a test, we found that only the multiplex methodology could show significant differences between populations in that case.

	P-Value
δ-band	0.701
θ-band	0.861
α-band	0.920
B-band	0.692
γ-band	0.771
Multiplex	**0.025**

In **Fig. 5**, the same statistical test was applied to the local participation coefficients. Only the significant differences (p-value < 0.05) between the two populations are coloured: blue when the HCs have a greater local participation coefficient than the ADs and purple inversely.

ROI	P-Value	Z-Score
G_cingul-Post-ventral R	0.003	-2.958
G_cuneus R	0.005	-2.800
G_front_inf-Triangul R	0.036	-2.097
G_front_sup R	0.049	1.972
G_insular_short L	0.036	-2.101
G_occipital_middle L	0.000	-3.773
G_parietal_sup R	0.006	-2.740
G_precentral L	0.039	-2.070
G_temp_sup-G_T_transv L	0.019	-2.346
Pole_temporal L	0.020	-2.327
S_central R	0.008	-2.673
S_front_inf L	0.009	-2.614
S_oc-temp_lat R	0.035	2.114
S_pericallosal L	0.002	-3.089
S_pericallosal R	0.002	-3.098
S_precentral-sup-part L	0.045	-2.005
S_temporal_sup L	0.004	-2.916

Integrating information from networks at different frequency bands has the potential to reveal novel insights into the organizational mechanisms of the brain. In this study, the proposed method was able to better discriminate between AD and HC groups, as compared to standard approaches [6].

This generic approach can find numerous other applications where the integration of different modalities (i.e. anatomical and functional) can inform new network models to ameliorate the comprehension of the organizational mechanisms in cognitive and clinical neuroscience [2].

▲ REFERENCES

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