Dynamics and functional connectivity in a network derived from anatomical data of the mouse brain

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Abstract: This project studies the collective dynamics of a neural network constructed from experimental connectivity data of the mouse brain. The Izhikevich model has been used to simulate the dynamics of neurons under different noise and excitatory strength conditions. The analysis has focused on how these parameters affect the global synchronization of the network, as well as on the comparison of three structural configurations: the original one, one with randomly redistributed connections, and another one with an eliminated module of the original network. From the activity data, functional matrices have been generated, and measures such as mean degree, global efficiency, and degree of modularity have been calculated. The results show how the structural properties influence the functional organization of the network and its synchronization capacity.

Keywords: Computational neuroscience, complex systems, Izhikevich model.
SDGs: 3, 4, 9 and 17.

I. INTRODUCTION

The brain is a complex network of synaptically connected neurons. Its cognitive functions depend not only on how individual neurons act but also on how they connect and interact with each other. Understanding how structure conditions or even determines functional dynamics is one of the main challenges of contemporary neuroscience [1]. Far from being uniform, the brain anatomy is characterized by a *modular* organization. A module refers to a neuronal cluster with high internal connectivity, which remains functionally interconnected with other modules. This structure allows the modules to process information in a specialized way but at the same time provides exchange of information via synchronization [2].

The advancement of techniques such as functional magnetic resonance imaging, tractography for diffusion imaging, and, at the microscopic level, fluorescent cell morphology reconstruction techniques enables the mapping of synaptic connections in the brain with high resolution. Specifically, recent work by Quian et al. (2024) [3] has made it possible to reconstruct the connectivity between individual neurons in the brain of a mouse, identifying potential connections through the spatial coincidence between axonal buttons and dendrites within a volume discretized into cubes with sides measuring 30 micrometers. These experimental data constitute an exceptional basis for computational modeling of the brain at the cellular level [3].

This project aims to study the dynamics of a real neural network obtained from the brain of a mouse. It simulates how the dynamics change under different network conditions. Each node does not represent an individual neuron but rather an aggregate unit. Both the connectivity between nodes and their spatial position are derived from experimental data [3]. The Izhikevich model is used for the dynamics, allowing the dynamic behavior to be simulated by treating each node as a neuron. Instead of explicitly modeling the connections and internal dynamics of each node, the set of neurons is considered to act as a single effective unit. The Izhikevich model achieves high biological fidelity with a simple structure that allows for high computational efficiency [4].

Overall, this approach integrates structure and dynamics to explore how the brain, even in simplified models, organizes its collective activity based on its synaptic architecture [1].

II. METHODS

A. Experimental data

For our specific data, high-resolution fluorescence microscopy was used to detect axonal boutons —synaptic points— to enable morphological reconstruction of 1,891 voxels at the scale of the entire mouse brain [3].

Briefly, brain volume is discretized into $30 \times 30 \times 30$ μm^3 cubes (*voxels*). A synaptic connection between voxels is established if the axonal boutons of the presynaptic voxel and the dendrites of the postsynaptic one coincide in the same cube. The synaptic weight between each pair of voxels is calculated as a product of the number of boutons of one voxel by the fraction of dendrites of the other within the cube, added over all the cubes of the brain [3]. These connections are presented as a list of pre- and post-synaptic pairs along with the associated connection strength and another list with the three-dimensional position of each voxel and the cerebral region to which they belong. The data used here was provided by Dr. Linus Manubes-Gil, researcher at Southeast University, Jiangsu, China.

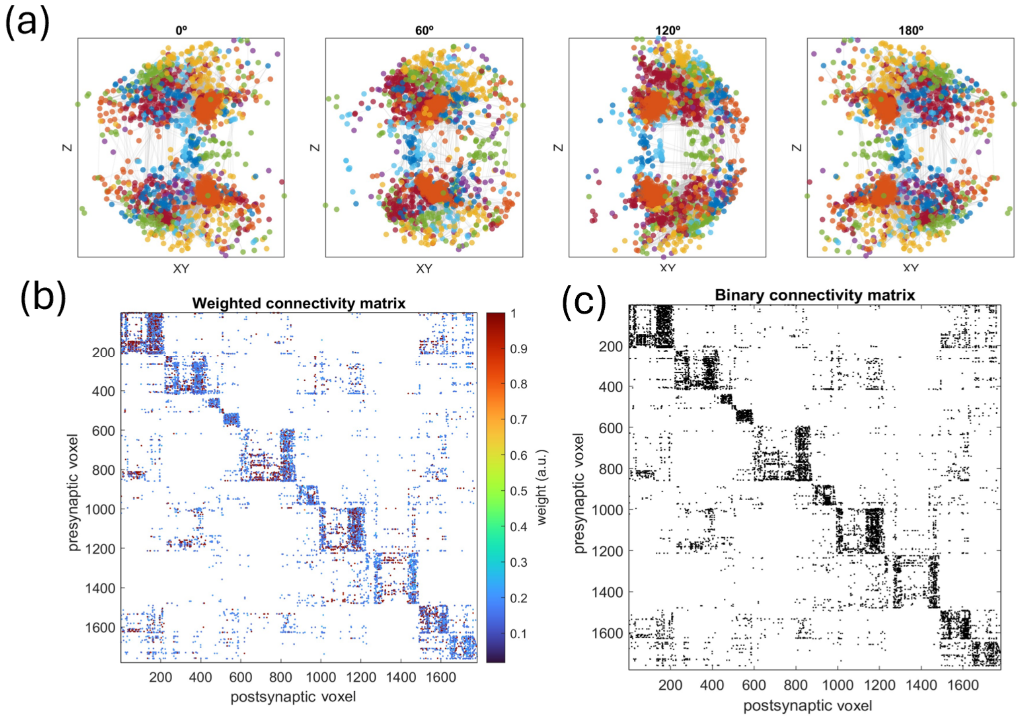

FIG. 1: (a) 3D visualization of voxels color-coded according to their brain region. Only the 10% strongest structural connections are shown to improve readability. Four views rotated on the XY plane are presented. (b) Weighted connectivity matrix (after logarithmic transformation and normalization) ordered by communities. The colors indicate the relative intensity of each connection. (c) Binary connectivity matrix, also sorted by communities. Each black dot indicates a structural connection.

B. Structural matrix

From the experimental data, a three-dimensional visualization is made to identify the spatial structure of the network and to observe the arrangement of the voxels according to their region of origin (Fig.1a).

In relation to the network structure, the binary and weighted connectivity matrices, A^B and A^W, respectively, are constructed. A^B simply accounts for the network core structure, i.e., who connects with who, whereas A^W incorporates the strength of the coupling. Each element A^W_{ij} of the weighted connectivity matrix contains the synaptic weight value between the presynaptic voxel i and the postsynaptic voxel j. As the synaptic weights cover several orders of magnitude, a logarithmic transformation is applied to all nonzero values of the matrix, A^W_{ij}. For that, all logarithms are scaled so that data is normalized between 0 and 1. Thus, the final weight, $\hat{w}_{ij}$, is obtained as:

$$\hat{w}_{ij} = \frac{\log(w_{ij}) - min(\log(A^W))}{max(\log(A^W)) - min(\log(A^W))},$$

where w_{ij} is the original weight between voxels and $max(\log(A^W))$ and $min(\log(A^W))$ are the maximum and minimum of all logarithms of the nonzero weights. Results are illustrated in Fig. 1b. The binary matrix A_B is also calculated (Fig. 1c), where $A^B_{ij} = 1$ indicates the existence of a synaptic connection from voxel i to voxel j, and $A^B_{ij} = 0$ otherwise.

Once the binary connectivity matrix is created, the analysis focuses on identifying the modular organization of the network. The aim is to detect *structural modules*, i.e., subnetworks in the structural network with a high density of internal connections and fewer connections with other communities. To implement Louvain's algorithm for modularity detection, a symmetric matrix is needed, so the A^B matrix is symmetrized as:

$$A^B_{sym} = \frac{1}{2}(A^B + A^{B^T}),$$

with A^B_{sym} the symmetric matrix and A^{B^T} the transpose. Applying the function `community_louvain` to A^B_{sym} gives the value of the modularity Q, explained below, and a vector with the module assigned to each voxel. The partition obtained is used to reorder the arrays so that the voxels are grouped by modules (Fig. 1b and Fig. 2c). This reordering facilitates the visualization of their modular structure and allows for a clearer comparison with the *functional* behaviour, described later, in which neuronal dynamics is run on the structural adjacency matrix.

C. Simulation of neural dynamics and synchronization

The Izhikevich model, a formulation based on differential equations that produce the electrical activity characteristic of cortical neurons, is used to model the dynamics of the network, enabling simulation of the dynamic behavior. For simplicity, each node of the structural network is treated as an 'effective neuron' that follows the Izhikevich description. A better approach would 'neural mass models', a mesoscopic approach for average activity in neuronal circuits, but their implementation is difficult. Thus, rather than explicitly modeling the connections and internal dynamics of each voxel, the ensemble of neurons within the voxel is considered to act as one effective 'Izhikevich' [4, 5].

The model is expressed by two equations that describe the membrane potential v, Eq. (1), and a recovery variable u, Eq. (2):

$$\frac{dv}{dt} = 0,04v^2 + 5v + 140 - u + I + \eta, \tag{1}$$

$$\frac{du}{dt} = a(bv - u), \tag{2}$$

where I represents the external input current and η a noise term that drives spontaneous activity. When v exceeds a threshold, a restart rule is activated that simulates a spike, i.e., a neuronal firing [4]:

$$\text{if } v \geq 30\text{mV, then } \begin{cases} v \leftarrow c, \\ u \leftarrow u + d. \end{cases}$$

The parameters (a, b, c, d) are predetermined constants that control the behavior of the system.

To build the network, 80% of voxels are defined as excitatory and 20% as inhibitory, according to real observations [1]. The main topological core, given by the experimental binary matrix A^B, is multiplied by a weight matrix W, generated with positive or negative values depending on the type of emitting voxel (excitatory or inhibitory). The final network is obtained as $S = A^B \circ W$. We note that W provides a simple way to add input strengths in a uniform manner across the network, which helps understanding the results. We could have used $S = A^W$ directly, but then it would have been very difficult to know whether network behavior was associated to the main neuronal topological wiring (just A^B) or their weights with a large dispersion of values, even with logarithmic scale.

From the S matrix, the dynamics of the network is simulated for 1000 ms, applying to each voxel the sum of synaptic inputs of the active presynaptic voxels, together with the Gaussian noise component η that drives spontaneous activity.

To study the effect of excitatory strength and noise, 200 values of each parameter are explored, resulting in 40,000 combinations. In each simulation, the concept of *global synchronization* is considered, defined as the percentage of voxels that fire within a 20 ms window. The maximum value of this series is recorded in a 200×200 synchronization matrix, represented as a colormap (Fig. 2a). In addition, two variants of the original connectivity matrix are generated: a randomized version, redistributing all existing connections uniformly among voxels, and another eliminating the connections of the voxels of the first detected structural module. For each variant, the global synchronization analysis is repeated, generating two additional 200×200 color maps that reflect the changes in activity under the same 40,000 combinations of excitatory strength and noise.

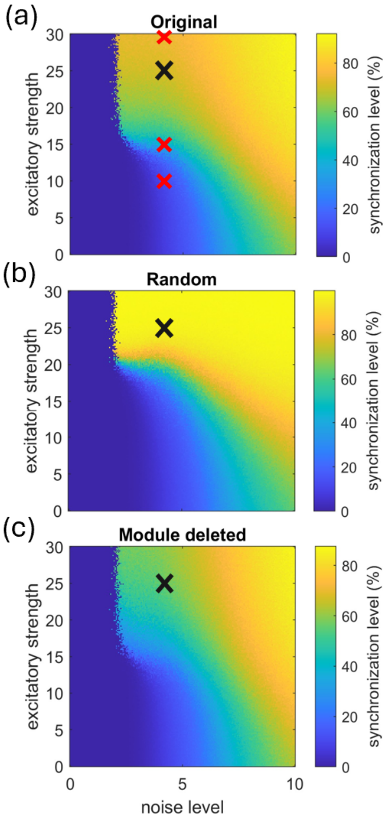

FIG. 2: **Global network synchronisation.** (a) Colormap of the maximum synchronization as a function of noise and excitatory strength for the original network. The red crosses are the points used to provide examples of network collective activity for the different excitation strengths in Fig. 3a. The black crosses are the points used to study the effect of synaptic structure on synchronization. (b) Colormap for the network with randomly redistributed connections. (c) Colormap obtained after eliminating a structural community.

D. Functional connectivity matrix

The simulated dynamics can be quantified through *functional connectivity* that reflects similar coactivation patterns between voxels. From the firing times, a binary activity matrix is generated where each voxel occupies a row and each column corresponds to a time instant. Then, the similarity between temporal patterns is calculated by applying Pearson's correlation coefficient to all pairs of voxels. This correlation measures the degree to which two activation series vary together, taking values between 0 and 1: values close to 1 indicate very simi-

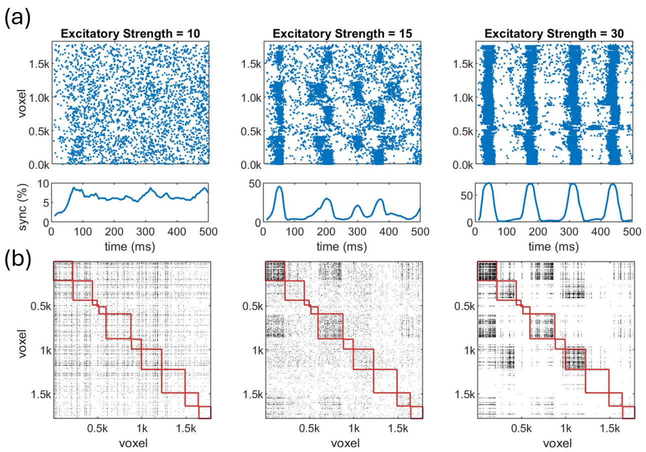

FIG. 3: **Network dynamics for three excitatory strength values.** (a) Raster plots showing the firing patterns for exc = 10, 15, and 30, with constant noise. As well as the time evolution of the synchronization for the three conditions above. (b) Binary functional matrices for the same conditions with outlined structural communities.

lar activations, while values close to 0 imply independent activity [6].

The correlation matrix is binarized by highlighting only the most relevant connections by taking the absolute value of the coefficients and selecting the top 5%, setting them as '1' and the rest as '0'. This procedure is repeated for three different scenarios (original structural network, random rewiring, and elimination of a module) and for three values of excitatory strength with constant noise. The order of the voxels is preserved according to the structural modules to facilitate their comparison.

E. Functional topological measures

From the binary functional matrices, different network indicators have been calculated to characterize its functional organization and to analyze how it changes under different structural conditions. The three global measures considered are:

- Mean degree: indicates the average number of functional connections that each voxel has. It is a basic measure of the functional density of the network.

- Global efficiency (G_E): quantifies how efficiently information can be transmitted between voxels. Networks with high global efficiency can propagate signals quickly between distant regions.

- Modularity (Q): measures the extent to which the functional network can be divided into well-defined *communities*, i.e., groups of voxels with high internal coactivity and low coactivity with other groups. It is used as an indicator of the presence of *functional modular organization.*

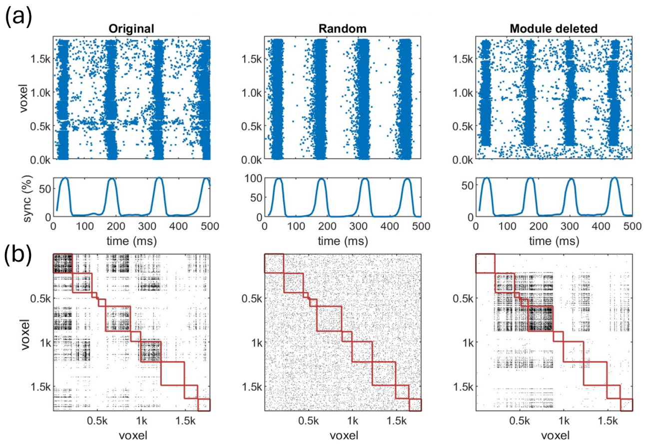

FIG. 4: **Dynamics for three different networks with constant parameters.** (a) Raster plots of the activity and evolution of synchrony over time for the original network, randomized and with one community deleted. (b) Corresponding functional matrices, with outlined functional communities of the original network.

These three measures have been calculated for the six simulation conditions mentioned above. This allows a comparison of how functional behavior varies with dynamics.

III. RESULTS

A. Activation regimes as a function of noise and excitatory strength

The global synchronization plot for the structural binary matrix (Fig. 2a) shows that the maximum synchronization occurs when the noise and excitatory strength are maximum (top-right corner). However, in this regime, the high noise may fully saturate activity. In addition, an intermediate region is observed where synchronization, although not maximal, is more varied (green band), as the noise facilitates synchronization without saturating the system. This reflects the fact that noise only acts as a promoter within a specific range. Indeed, too little noise does not reach the threshold necessary to trigger synchronization (blue region).

Exc.	**Mean degree**	**Efficiency G_E**	**Modularity Q**
10	85,881	0,454	0,238
15	87,113	0,465	0,253
30	87,111	0,126	0,409

TABLE I: Functional topological measurements for the original network. Comparison of the mean degree, global efficiency, and modularity for three values of excitatory strength and with a constant noise value set to $\eta = 4$.

To analyze in more detail how the dynamics of the network vary according to the excitatory strength, three representative configurations have been selected, marked with red crosses in Fig. 2a (Exc = 10, 15, and 30; constant noise $\eta = 4$). The corresponding raster plots (Fig. 3a) show that at Exc = 10 the neural activity is very low and dispersed. At Exc = 15, groups of synchronously firing voxels appear, probably corresponding to structural modules, but without the whole network being coordinated. At Exc = 30, practically all voxels participate in collective episodes, and the synchrony peaks (Fig. 3a) are more marked and frequent, indicating a much more global and synchronized activity.

This pattern is also reflected in the functional matrices (Fig. 3b). At Exc = 10, no clear structure can be distinguished. At Exc = 15, some functional communities emerge and that even match structural organization, especially the first module and others, that are more diffuse. At Exc = 30, the functional communities are much more defined and segmented, and not all of them coincide with the structural modules. Topological measures (Table I) corroborate that: with increasing excitatory strength, functional Q increases progressively, while overall efficiency G_E decreases, suggesting that activity is fragmented into strongly synchronized but less connected internal modules.

B. Effect of synaptic structure on synchronization

To evaluate how synaptic structure determines collective dynamics, we compared the original network with two variants: one with randomly redistributed connections (randomized network) and another where all connections of a community (voxels 1 to 238) have been removed. The results show that the random network (Fig. 2b) has a higher global synchronization than the original one, especially at high excitation levels. However, this synchronization occurs without a defined structure, as indicated by the functional modularity (Table II), which drops to $Q = 0.148$. In contrast, the overall efficiency increases ($G_E = 0.502$), and the mean degree is also slightly higher. This pattern reflects an increase in the overall spread of activity, but with less functional segregation.

Network	Mean degree	Efficiency	Modularity
Original	86,814	0,176	0,410
Random	89,003	0,502	0,148
Module deleted	86,420	0,131	0,150

TABLE II: Functional topological measurements for three networks. Comparison of the mean degree, global efficiency, and modularity for the original network, the randomized network, and the network with a deleted module.

The elimination of a structural community (Fig. 2c and Table 2) causes a generalized decrease in synchronization, with particular impact on the intermediate values where the original network showed maxima. Even though they have a similar mean degree as the original network, global efficiency and modularity are lower. This shows the functional importance of certain structural groups within the network.

IV. CONCLUSIONS

This project has allowed us to analyze how the structural connectivity of a neural network affects its functional behavior, based on experimental data from the mouse brain. Simulations with the Izhikevich model have shown a dependence between excitatory strength, noise, and the ability of the system to synchronize. In particular, it has been observed that there are certain regions of the parameter space where collective synchronization is maximal.

A comparison between different synaptic structures shows that reorganizing connections and removing a community affects global functional properties, like modularity and global efficiency. This study emphasizes the importance of integrating structure and dynamics to better understand how neural activity is coordinated in complex networks.

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Dinàmica i connectivitat funcional en una xarxa derivada de dades anatòmiques del cervell del ratolí

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Resum: Aquest projecte estudia la dinàmica global d'una xarxa neuronal obtinguda a partir de dades experimentals del cervell d'un ratolí. L'activitat neuronal se simula mitjançant el model Izhikevich. S'avalua quin impacte té sobre la sincronització global diferents condicions de força excitadora i soroll. L'estudi compara tres configuracions estructurals de la xarxa: l'original, una versió amb connexions aleatòries i una altra amb un mòdul eliminat. A partir de l'activitat neuronal resultant, es generen matrius de connectivitat funcional. Es caracteritza cada xarxa i combinació de força i soroll a partir de mesures com el grau mitjà, l'eficiència global i la modularitat. Comparant les mesures topològiques i les gràfiques veiem com canvis estructurals en la xarxa tenen efecte en la dinàmica i la connectivitat funcional de la xarxa.

Paraules clau: Neurociència computacional, sistemes complexos, model d'Izhikevich.
ODSs: 3,4,9 i 17.

Objectius de Desenvolupament Sostenible (ODSs o SDGs)

1. Fi de la es desigualtats		10. Reducció de les desigualtats	
2. Fam zero		11. Ciutats i comunitats sostenibles	
3. Salut i benestar	X	12. Consum i producció responsables	
4. Educació de qualitat	X	13. Acció climàtica	
5. Igualtat de gènere		14. Vida submarina	
6. Aigua neta i sanejament		15. Vida terrestre	
7. Energia neta i sostenible		16. Pau, justícia i institucions sòlides	
8. Treball digne i creixement econòmic		17. Aliança pels objectius	X
9. Indústria, innovació, infraestructures	X		

El contingut d'aquest TFG, part d'un grau universitari de Física, es relaciona amb l'ODS 3, meta 3.2, donat que reforça la capacitat científica per a la comprensió del funcionament del cervell. També està vinculat amb l'ODS 4, amb la fita 4.4, ja que contribueix a l'educació a nivell universitari. Respecte a l'ODS 9,recolza la meta 9.5 en promoure la investigació científica i el desenvolupament tecnològic en el camp de la neurociència computacional. Finalment, contribueix a l'ODS 17, meta 17.6, en basar-se en la col·laboració internacional i l'ús compartit de dades experimentals entre institucions.