

Supplementary Material of the paper "Patient-specific network connectivity combined with a next generation neural mass model to test clinical hypothesis of seizure propagation"

Moritz Gerster ¹ **, Halgurd Taher** ² **, Anton´ın Skoch ˇ** ³ **, Jaroslav Hlinka** ³,⁴ **, Maxime Guye** ⁵,⁶ **, Fabrice Bartolomei** ⁷ **, Viktor Jirsa** ⁸ **, Anna Zakharova** ¹ **and Simona Olmi** ²,9,[∗]

¹ Institut für Theoretische Physik, Technische Universität Berlin, Hardenbergstr. 36, *10623 Berlin*

² Inria Sophia Antipolis Méditerranée Research Centre, MathNeuro Team, 2004 *route des Lucioles-Boˆıte Postale 93 06902 Sophia Antipolis, Cedex, France*

³ *National Institute of Mental Health, Topolova 748, 250 67 Klecany, Czech Republic ´*

4 *Institute of Computer Science of the Czech Academy of Sciences, Pod*

Vodarenskou vezi 2, 18207 Prague 8, Czech Republic

⁵ Faculté de Médecine de la Timone, centre de Résonance Magnétique et *Biologique et Medicale (CRMBM, UMR CNRS-AMU 7339), Medical School of ´ Marseille, Aix-Marseille Universite, 13005, Marseille, France ´*

⁶ *Assistance Publique -Hopitaux de Marseille, H ˆ opital de la Timone, P ˆ ole d'Imagerie, ˆ CHU, 13005, Marseille, France*

⁷ *Assistance Publique - Hopitaux de Marseille, H ˆ opital de la Timone, Service de ˆ Neurophysiologie Clinique, CHU, 13005 Marseille, France*

8 Aix Marseille Université, Inserm, Institut de Neurosciences des Systèmes, UMRS *1106, 13005, Marseille, France*

⁹ *CNR - Consiglio Nazionale delle Ricerche - Istituto dei Sistemi Complessi, 50019, Sesto Fiorentino, Italy*

Correspondence*: Simona Olmi simona.olmi@fi.isc.cnr.it

1 MINIMAL BIOPHYSICAL MODELS OF SEIZURE DYNAMICS

The detection of epileptic seizures via electrophysiological recordings allowed for the establishment of a detailed taxonomy of seizures. The majority of seizures recorded in humans and experimental animal models can be described by a generic phenomenological mathematical model, the Epileptor [\(Jirsa et al.,](#page-2-0) [2014\)](#page-2-0). In this model, seizure events are driven by a slow permittivity variable and occur via saddle node and homoclinic bifurcations at seizure onset and offset, respectively. The saddle-node bifurcation at the onset of ictal discharges was chosen based on experimentally observed features, such as fixed frequency and fixed amplitude of abruptly starting oscillations, and a shift of baseline field potential. The homoclinic bifurcation

at the offset of ictal discharges, on the other hand, reproduces the logarithmic scaling of interspike intervals when approaching seizure offset. As part of the dynamic repertoire of the Epileptor, the epileptic attractor is described in terms of a self-sustained limit cycle that comes from the destabilisation of the physiological activity while multiple types of transitions allow for the accessibility of seizure activity, status epilepticus and depolarization block, that coexist, as verified experimentally in [\(El Houssaini et al., 2020\)](#page-2-1).

The Epileptor model has been reduced to a minimal canonical mathematical representation of high codimension (up to 4) that, appropriately tuned, can display several types of fast-slow behaviors [\(Saggio](#page-2-2) [et al., 2017\)](#page-2-2). The model contains two subsystems acting at different time scales, in which the fast subsystem is unfolded in a plane showing several bifurcation paths of a high codimension singularity. The slow subsystem steers the fast one back and forth along these paths leading to fast-slow (aka bursting) behavior, mimicking epileptiform activity. The model is able to produce almost all the classes of bursting predicted for systems with a planar fast subsystem, including the Epileptor class, and has been demonstrated to be the dominant class, so-called dynamotype, in empirical epilepsy data [\(Saggio et al., 2020\)](#page-2-3). Other dynamotypes have been also found empirically.

When performing the analysis of the single-population firing rate equations (4), it turns out that, in the absence of forcing, the only attractors are fixed points. As it becomes clear in the Section 3 of the Main Text, a stable node and a stable focus are observable, separated by a bistability region between a high- and a low-activity state, whose boundaries are the locus of a saddle-node bifurcation (for more details see [\(Montbrio et al., 2015\)](#page-2-4)). In this context, self-sustained oscillations are not observable, but only damped oscillations at the macroscopic level that reflect the oscillatory decay to the stable fixed point. This oscillatory decay will here be considered as representative of a seizure-like event, not being able to observe a stable limit cycle to describe the emergence of a fully developed seizure as in the Epileptor. However, seizure-like events can be used as paradigm to investigate propagation of seizure-like activity in the network. Furthermore, a recently developed model of interictal and ictal discharges, called Epileptor-2 [\(Chizhov et al., 2018\)](#page-2-5), makes links to underlying physiology and suggests how to eventually obtain all observed dynamotypes for the exact neural mass model Eqs. (4) and enable transitions towards fully developed seizure activity.

Epileptor-2 is a simple population-type model that includes four principal variables, i.e. the extracellular potassium concentration, the intracellular sodium concentration, the membrane potential and the synaptic resource diminishing due to short-term synaptic depression. A QIF neuron model, whose dynamics is ruled by an equation similar to Eq. (1), is used as an observer of the population activity. While the potassium accumulation governs the transition from the silent state to the state of ictal discharge, the sodium accumulated during the discharge, activates the sodium-potassium pump, which terminates the ictal discharge by restoring the potassium gradient, thus polarizing the neuronal membranes. This means that, in high potassium conditions, Epileptor-2 produces bursts of bursts, described as ictal-like discharges.

Therefore, the association of a slow subsystem describing ion concentration variations together with a fast subsystem, identified by Eqs. (4), should give rise to self-emergent periodic and bursting dynamics at the macroscopic level, thus allowing us to identify different combinations of onset/offset bifurcations. Whenever not sufficient, it will be possible to investigate the dynamics emergent in the exact neural mass model, provided with short-term synaptic plasticity, when subject to a global feedback acting on a slow timescale, describing ion concentration variations. The exact neural mass model, when equipped with short-term synaptic plasticity, shows a more complex dynamics that eventually results in a bifurcation diagram that provides stable limit cycles [\(Taher et al., 2020\)](#page-2-6). However the introduction of short-term

plasticity, itself, adds complexity to the dynamics, allowing for the emergence of bursting activity [\(Tsodyks](#page-2-7) [et al., 1998\)](#page-2-7).

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SUPPLEMENTARY TABLES AND FIGURES

Table 1. Cortical and subcortical regions, according to the Automated Anatomical Labeling atlas 1(AAL1) [\(Tzourio-Mazoyer et al., 2002\)](#page-2-8). Odd/even numbers correspond to the left/right hemisphere.

Table 2. Cortical and subcortical regions, according to the Desikan-Killiany atlas [\(Desikan et al., 2006\)](#page-2-9).

Table 3. Clinical characteristics of the patients. N, normal; L, left; R, right; Th, thermocoagulation; Gk, Gamma knife; Sr, surgical resection; NO, not operated; PVH, periventricular nodular heterotopia; FCD, focal cortical dysplasia; SPC, superior parietal cortex; F, Frontal; NA, not available.

Table 4. Results of propagation zone prediction for each patient. Abbreviations are given in Supplementary Table [2.](#page-4-0)

Figure 1. Number of recruited brain areas as a function of the excitability parameter $\bar{\eta}_G$ for 5 exemplary healthy subject connectomes and increasing Gaussian standard deviation. Here is reported a numerical experiment equivalent to the one shown in Fig. 3 (Main Text), where $\bar{\eta}_G$ represents the mean value of a Gaussian distribution with increasing standard deviations σ_{G} . (A1-E1) $\sigma_{\text{G}} = 0.3$; (A2-E2) $\sigma_{\rm G} = 0.5$; (A3-E3) $\sigma_{\rm G} = 1$. Color coding is the following: blue corresponds to the asymptomatic threshold (one area in HA regime); red represents 90 areas in HA regime (generalized threshold); cyan to purple indicate intermediate recruitment values, white marks no recruitment. For very large values of $\bar{\eta}_G$ (usually $\bar{\eta}_G > -5$), the system enters the stable focus regime before the stimulation is applied. In that case $\bar{\eta}^{(k)}_\text{gen}$ is not defined because no brain areas are recruited as a result of the applied stimulation current: for this reason white color, corresponding to no recruited areas, is visible also in the right part of the different panels. For increasing standard deviation values, the effective excitability of the more and more nodes turn out to be close to the one that allows the system to be in the stable focus regime, therefore the probability of finding nodes in the stable focus regime increases. As a result, more and more nodes enter the HA state and recruite the other areas before the stimulation current is applied. This means that for increasing standard deviation, $\bar{\eta}^{(k)}_{\rm gen}$ become less defined while $\bar{\eta}^{(k)}_{\rm asy}$ move to larger values of $\bar{\eta}_G$, still remaining better identifiable for increasing heterogeneity. As in Fig. 3, A), B), C), D), and E) correspond respectively to subjects H1, H5, H12, H16, and H19. Parameters: $N_{\text{pop}} = 90, \Delta = 1, \sigma = 1, I_S = 10, t_I = 0.4$ s.

Figure 2. Network measure correlations of healthy subjects. Panels A-F are obtained plotting independently all node values for all the subjects $(90*20=1800)$ data points). Panel G: Data are averaged over all 20 subjects. The single node values are averaged over the different subjects and afterwards, the correlation between node strength and clustering coefficient is estimated. Infinite values were excluded. The Pearson correlation of clustering coefficient and node strength of the averaged healthy DTI topology is $r = 0.9$ and much stronger compared to the average of all individual topologies $r = 0.75$ from panel A.

Figure 3. Weight Distribution of the DTI graphs. The weight distribution with weights on the x-axis in ascending order. a) Weight distribution, b) the inverse weight distribution, c) and the logarithmic weight distribution of the healthy averaged DTI graph. Note that c) matches the curve of recruitment times in Fig. 6 A) in the Main Text.

Figure 4. Input Current Duration Variation. Dependence of the recruitment time on the current duration t_I while the current strength is kept constant at $I_S = 15$. The y-axis shows the recruitment times of the first 10 recruited areas for each current strength. Blue is the EZ, green is the first recruited area, red the second, etc. The recruitment times are independent of the pulse duration. Parameters: $N_{\text{pop}} = 90$, $\sigma = 1$, $\Delta = 1$, $\bar{\eta} = -6$, $I_{\rm S} = 15$, stimulation site: brain area $k = 45$ for the healthy H1.

Figure 5. Statistical significance of PZ_{SEEG} and PZ_{clin} recruitment times. The figure shows the recruitment times of all brain areas on the y-axis. Blue (orange) dots correspond to PZ_{SEEG} (PZ_{clip}). The grey dots correspond to all brain areas except for the EZ and the areas identified as PZ_{SEEG} ; the white dots to all brain areas except for the EZ and the areas identified as PZ_{Clin}. Note that some brain areas of the PZ are either identified as PZ_{SEEG} or PZ_{Clin} while others are identified as both PZ_{SEEG} and PZ_{Clin} . Therefore the set of grey and white dots is very similar but not identical. A one-sided Mann-Whitney U test detected significantly earlier recruitment of the PZ_{SEEG} ($p < 0.05$) for patients E1, E2, E4, E5, E8, and E9. For the PZ _{Clin}, the recruitment was significantly earlier for all patients.

Table 5. List of the first 10 recruited brain areas for each patient. The column "Type" indicates whether the recruited area belongs to the estimated PZ via presurgical invasive (PZ_{SEEG}) or non-invasive (PZ_{Clin}) evaluation.
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Frontiers **Table 7.** Continued from Tables [5,](#page-10-0) [6.](#page-11-0) **Frontiers 13**

Figure 6. Recruitment times for patient E2 obtained for 6 different random Gaussian distributions of $\bar{\eta}$. (A1-F1) Spacetime plots of the average firing rates of all brain areas. (A2-F2) Histograms of the recruitment times. Orange (blue) bins identify those recruited area that belong to PZ_{Clin} (PZ_{SREG}). (A3-F3) Cumulative histograms of the recruitment times. Orange bins: first 10 recruited areas. Parameters as in Fig. 10 (Main Text). For one exemplary patient, E2, we show here in detail the impact of different realizations of $\bar{\eta}^{(k)}$, drawn from a Gaussian distribution (centred at $\bar{\eta}_G = -7.5$ with standard deviation 0.1), on the recruitment times of the brain areas. In particular we have considered it to be sufficient to present results for six out of ten realizations, due to the large similarities between the outcomes. Space-time plots of the average firing rates give an immediate visualization of the recruitment events for each brain area. We find that the pattern of recruitment does not change substantially for different realizations of the $\bar{\eta}^{(k)}$. The EZ is localized in the area lh-LOCC, that corresponds to node $k = 21$. The firing rate of this population increases immediately upon stimulation, thus giving rise to the recruitment mechanism. The brain areas in the PZ are rapidly recruited: In general the first ten areas are always recruited in less then 0.1s, followed by a continuous increase of the number of recruited nodes. Finally, it is worth noticing that the first recruited areas correspond to those predicted clinically.

Figure 7. Graph plots for the epileptic patients with more than one area in the EZ. Same as Fig. 12 (Main Text) but for the patients with more than one area in the EZ (yellow node). All areas belonging to the EZ are merged into one for visualization clarity, keeping intact the recruitment order, the recruitment times and the connection weights to the areas in the EZ. Node circle size corresponds to the inverse recruitment time (A1-D1), to the connection strength to the EZ (A2-D2) and to the inverse shortest path length to the EZ (A3-D3). The size of the yellow EZ circle remains fixed. Blue dots distinguish recruited areas to belong to the PZ $_{SEEG}$, i.e. the PZ identified according to the presurgical invasive evaluation. Results are obtained for patients E1 (panels A1-A3), E4 (panels B1-B3), E5 (panels C1-C3), E7 (panels D1-D3). Note that patient E1 has very weak connections outgoing the EZ which results in very late recruitment times indicated by small circle sizes in A1. For patient E4, the first ten recruited nodes are strongly connected with the EZ. The recruitment of node 31 before node 80 (stronger connected to the EZ with respect to the previous one), is justified by the strong connection to node 36 and the comparable shortest path length. For patient E5 the shortest path length is more determinant than the connection strength to the EZ to determine the recruitment order. The sequentially recruited nodes are particularly strongly connected, thus explaining the recruitment of node 17, weakly connected to the EZ, but strongly connected to the previously recruited node. Patient E4, on the other hand, has very strong connections outgoing the EZ and very short recruitment times indicated by large circle sizes in B1. As shown in Fig. 12, the first recruited node is usually the one with the strongest connection strength to the EZ and with the shortest path to the EZ (apart for the case B3). Parameters as in Fig. 10 (Main Text).

Figure 8. Graph plots for the epileptic patients with more than one area in the EZ. Same as figure [7](#page-14-0) but for patients E8 (panels A1-A3), E9 (panels B1-B3), E10 (panels C1-C3), E11 (panels D1-D3). For patient E8, the first two recruited areas show strong connection strengths to the EZ, while the areas recruited later are all characterized by shortest path to the EZ and by strong connections between sequentially recruited nodes. Looking at the graph plots for patient E9, the first four recruited nodes are both strongly connected with the EZ and among them. Node , which do not result to belong to the PZ_{SEEG}, is recruited, according to our simulations, due to its topological characteristics: proximity to the EZ, in terms of shortest path length, and high coupling strength. For patient E10, the node 70 (belonging to the PZ_{SEEG}), do not result to be first recruited due to its middle values of connection strength and shortest path, while the nodes that are recruited before are either more strongly connected to the EZ or to the previously recruited node. For patient E11 the recruitment order is mostly determined, as before, by the shortest path length and by the connection strength between sequentially recruited node. As shown in Fig. 12 (Main Text), the first recruited node, for all patients, is the one with the strongest connection strength to the EZ and with the shortest path to the EZ. Parameters as in Fig. 10 (Main Text).

Figure 9. Graph plots for the epileptic patients with more than one area in the EZ. Same as figure but for patients E12 (panels A1-A3), E14 (panels B1-B3), E15 (panels C1-C3). For patients E12 and E15 the recruitment order is mostly determined by the shortest path length to the EZ, supported by the connection strength, which results to be determinant for the first $4-5$ recruited nodes. Node 77 , belonging to the PZ_{SREG} for patient E15, do not result to be first recruited due to its middle values of connection strength and shortest path, while the nodes that are recruited before are either more strongly connected to the EZ or to the previously recruited node. On the other hand, for patient E14, the connection strength turns out to be more important than the shortest path to determine the recruitment order. It is worth noticing that node 24, closer to the EZ and strongly connected to node 18, is recruited before nodes 22 and 39 that are more strongly connected to the EZ, but less close in terms of shortest path. As shown in Fig. 12 (Main Text), the first recruited node is usually the one with the strongest connection strength to the EZ and with the shortest path to the EZ (apart for the case B3). Parameters as in Fig. 10 (Main Text).

Figure 10. Recruitment time and Shortest Path. The recruitment times t_{rec} as a function of the shortest path to the EZ are shown for four patients and all brain areas. Same as Fig. 13 A (Main Text), with a regression fit that underlines the approximately linear relationship between the shortest path length and the recruitment time. Spearman correlation coefficients ρ and corresponding p-values are significant. Parameters as in Fig. 13 (Main Text).

Figure 11. Input Current Duration Variation. Dependence of the recruitment time on the current duration t_I , while the current strength is kept constant at $I_S = 15$, for epileptic patients A) E2; B) E3; C) E6; D) E13. The y-axis shows the recruitment times of the first 10 recruited areas for each current strength. Blue is the EZ, green is the first recruited area, red the second, etc. The recruitment times are independent of the pulse duration. Parameters: $\sigma = 4$, $\Delta = 1$, $\bar{\eta} = -12.5$, $I_S = 15$.