Roskilde University, Universitetsvej 1
4000 Roskilde Denmark

Project in Science
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Modeling of signal propagation through networks of neurons

Anakin Diermayr, Alex Winter, Konstantina Kalagia, Svetlana Rusnakova, Kenni Abild, and Ana Helena Vieira de Melo Gomes Prata
Supervisor: Carsten Lunde Petersen

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Seizure

Seizures can be primarily interpreted as a dynamical disease [**da2003epilepsies**, **milton2010epilepsy**] and computational models have been successful in gaining insight into and generate hypothesis to the cellular and network level brain mechanisms of seizures [**bazhenov2008cellular**].

Definition and classification of seizures

The role of neuronal networks in seizure generation

(or network effects)

- network properties influence seizure dynamics –> connectivity and coupling strengths

Some notes: - The role of neuronal networks in seizure generation - Models for simulating seizures - A chaotic process can be classified according to its fractal dimensions and Lyapunov exponent [**du2013neural**]. - Identifying bifurcation points in neural systems

When modeling neuronal interactions, and in particular modeling of seizures, the model must reflect the fact that thousands of neurons need to interact in order to display seizure-like activity. The first major roadblock becomes the quantity of neurons involved, it is not possible to measure the activity of every individual neuron, even assuming one could do so, it would be a monumental task to extract useful information from the bulk. Therefore we must be smart about creating a model, choosing the 'right' approach to simplify the equations can save astronomical amounts of time and effort.

1. **Model average activity**
2. **Reduce parameter space**
3. **Tackle a smaller problem**

A system can be modeled deterministicly or contain stochasticly. When collecting data, measurements will rarely be completely deterministic. This is not because forces act in unpredictable manner, rather that there exists far too many elements in the 'real' world for any model to fully account for them. As a consequence, many models will incorporate both deterministic and stochastic elements to more accurately reflect the observed data.

1. **Model simplification**
2. **Stochastic activity**
3. **stochastic Inputs**

4.1 Physiological Parameters

It's important to determine what is even being modeled, which features can be parameterized and which can not.

4.2 Parameters of Neural Models

When it comes to modelling the brain activity it is essential to present a set of variables and parameters apropos of the previously chosen dynamic model. The model usually consists of a system of equations, able to describe and predict a model behavior over some specific time frame. But simulating any kind of brain dynamics is in principle a challenging task and therefore one should follow some guidelines for deciding upon the complexity of the model. The goal is to make it as composite as possible to sufficiently describe its machinery but at the same time adequately easy, to be computable by current computing methods. The latter is in fact a prerequisite.

$$\frac{d\mathbf{z}(t)}{dt} = P(\mathbf{z}(t), \kappa(t), u(t), t) \tag{4.1}$$

Each dynamic brain model may be represented by the continuous-time state-transition equation. In this standard format, one may determine the intricacy of the model, by means how much detail should or should not it be included, by varying its components. The formula depicts the development of the state $\mathbf{z}(t)$, with a parameter set $\kappa(t)$, and an input $u(t)$. The model's behavior is then determined by the mapping P.

- In the process of studying the model, the aim is to investigate changes in the system *variables*, which, in dynamical models, are absorbed in the state $\mathbf{z}(t)$. These changes happen only via the evolving relationships encoded in mathematical formulas, while alterations in parameters arise from external sources beyond the model's scope.
- *Parameters* $\kappa(t)$, on the other hand, are attributes of the state, that can be empirically measured. They are placeholders that constitute to values in the group of maps P (mapping or mapplet) [Informatica® Cloud Data Integration November 2023 Mappings]. They are used when it is necessary to keep values constant in time, or during desired observation. In real life, however, the values of parameters (and variables) can vary, but parameters deviate at a different pace than variables. It is reasonable that the parameters and time-dependency are to be related.

There exists no predetermined set of rules dictating what features ought to function as parameters and which should operate as variables, however, a certain group of general instructions can be considered.

1. It can be acknowledged that parameters may exhibit very steady variations, compared to the relevant temporal horizon, for instance, the network's neuron count remains relatively stable, when working in short time intervals. Yet, in a lifespan of a couple of years, some neurons will annihilate, affecting the overall number of brain cell communities. Hence, it is necessary to match a specific time scale with a corresponding parameter, failing to do so may justify its classification as variables. Nevertheless, parameters are typically considered to remain constant over the interval. At certain times, this holds accurately. An example would be an axon's length, that stays fairly permanent as time evolves. It brings some degree of simplicity into the model, particularly in the course of analysis.

2. Usually, reasonable approximations already exist for both variables and parameters. The values of parameters can normally be determined from observational data. In cases where values are not obtainable, there still happen to be lifelike limitations. Variables, on the contrary, are investigatory quantities with a broad range of plausible values. Even if estimates are available, it proves challenging to see the impact of minor changes on a system.

4.2.1 - One neuron

In the spatial scale of one neuron, the choice of the model itself decides on the parameters that are to be used. The integrate-and-fire model is relatively straightforward. The excitatory and inhibitory currents representing the input are entering the branches of dendrites. They are added up at the soma, which embodies the integration process. If the value reaches a certain threshold, the action potential is fired to serve as the resultant outcome. The relevant set of parameters are ones responsible for producing the action potential.

5 Our Approach

6 Methodology

In order to investigate further the models in terms of applicability, scalability and accuracy, among other factors, there was a need to run computer simulations where parameters can be easily changed and their effects on models are easier to compare.
Python was the chosen language to do so. It is of free-access, unlike Mathlab which requires a license, more prominent than Octave(so more resources are available), and very versatile. Since, machine learning was also considered, R was deemed as not as suitable as Python. It is a statistical programming language. Moreover, the numba and numpy libraries which are based on C/C++ code make it relatively fast.
As such, python simulations were performed as this language is very well-documented, approachable and already widely used in data analysis. From the scripts, one can create phase planes and graphs to better visualize the behaviour of variables within the model.

7 Results

Part II

Discussion

8 Model Discussion

8.1 Fithugh-Nagamo

8.2 Chay

8.3 Hodgkin-Huxley

8.4 Choice of model

9 Coupling

10 Conclusion

Appendix

.1 Images