Automatic adaptation and mappings of hybrid circuits

CNS 2020 Closed-Loop Neuroscience Tutorial

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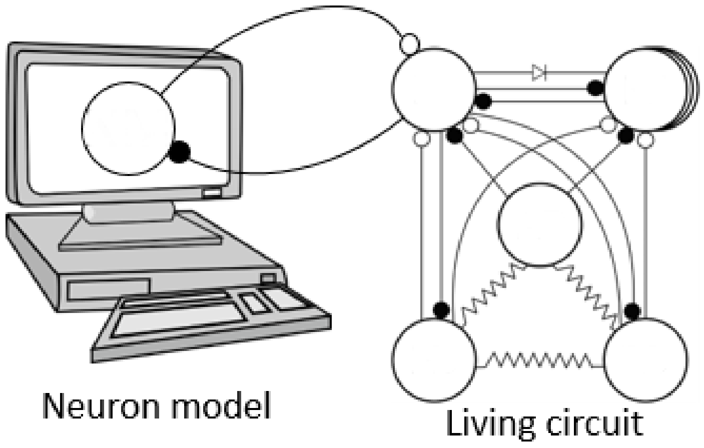
Hybrid circuits

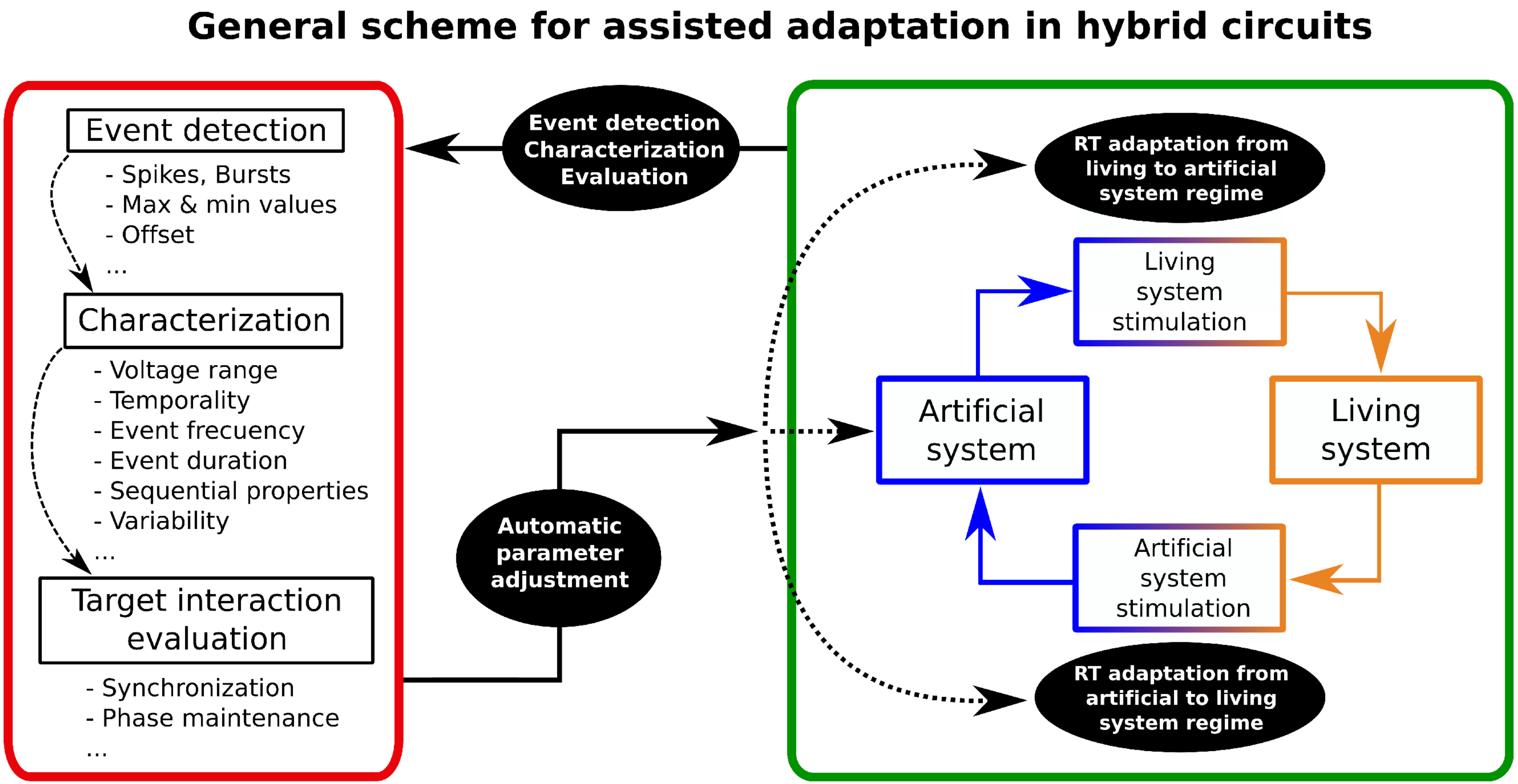
- **Hybrid circuits** are built by connecting **living and model neurons**.
- These circuits have a lot of potential in neuroscience but **require complex adaptations** to work properly.
- Here we present a set of **algorithms to facilitate and diseminate building and using hybrid circuits.**
- The proposed **dynamic adaptation can be generalized to other hybrid circuits and closed-loop protocols** among living and model neural systems.

Hybrid circuits are difficult to build



Parameters and calibration are usually set manually

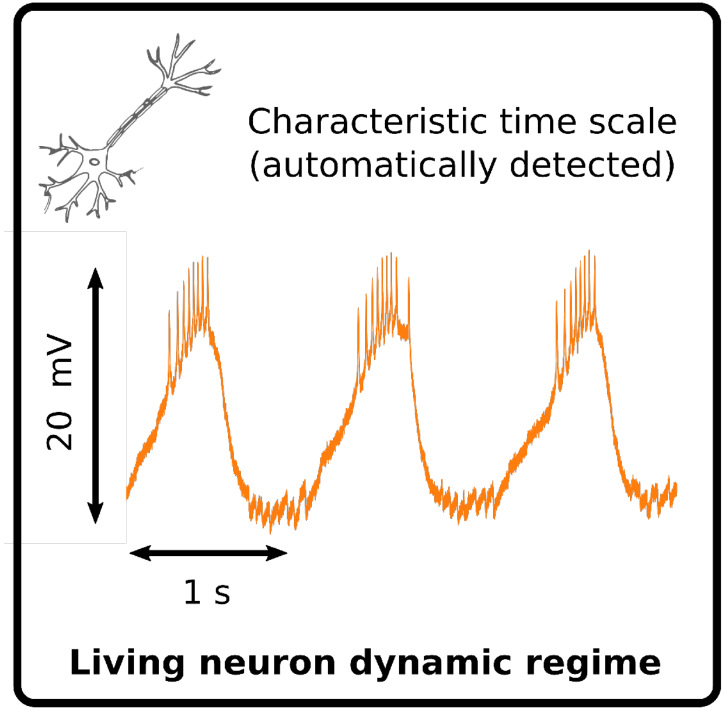
Closed-loop automatic adaptations



Reyes-Sanchez, M., Amaducci, R., Elices, I., Rodriguez, F. B., & Varona, P. (2020). Automatic Adaptation of Model Neurons and Connections to Build Hybrid Circuits with Living Networks. Neuroinformatics, 18(3), 377–393. Link

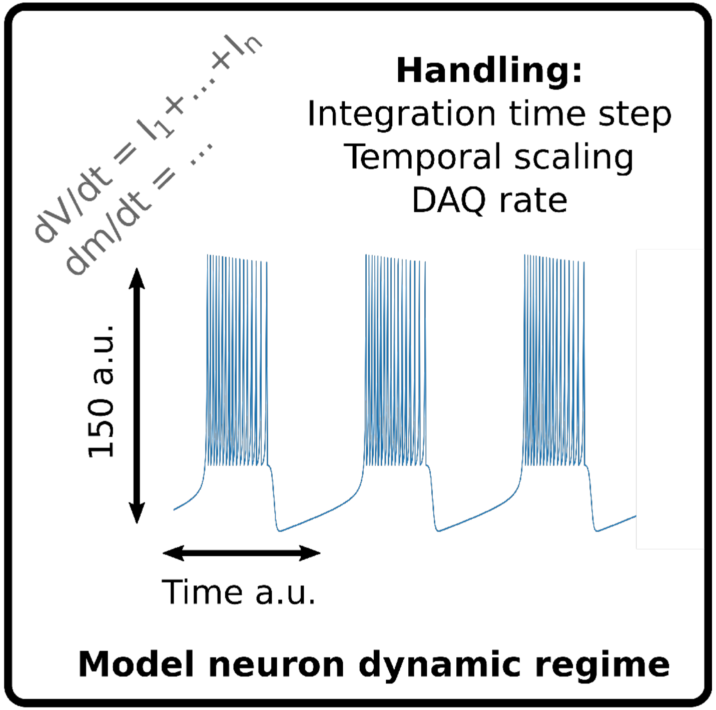
Closed-loop automatic adaptations

Living neurons and models have different spacial and temporal scales!



Temporal & amplitude scaling

Current adaptation

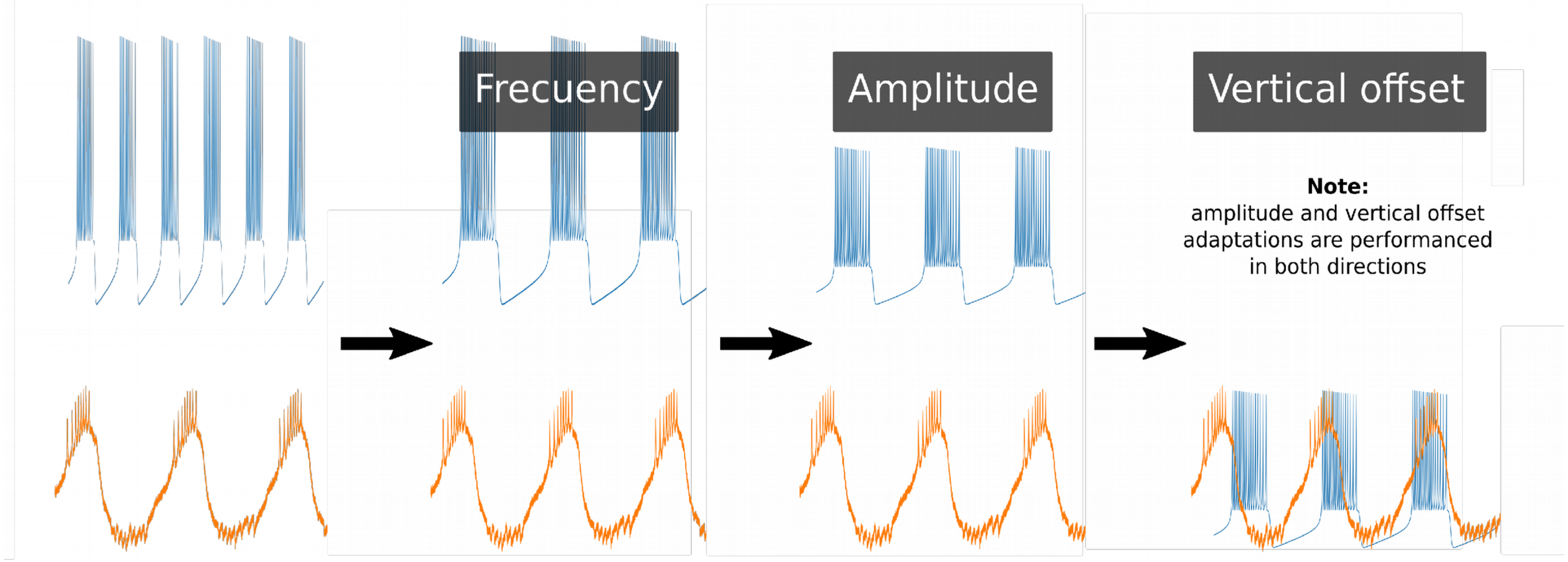


Need for automatic calibration and parameterization

Automatic time and amplitude scaling

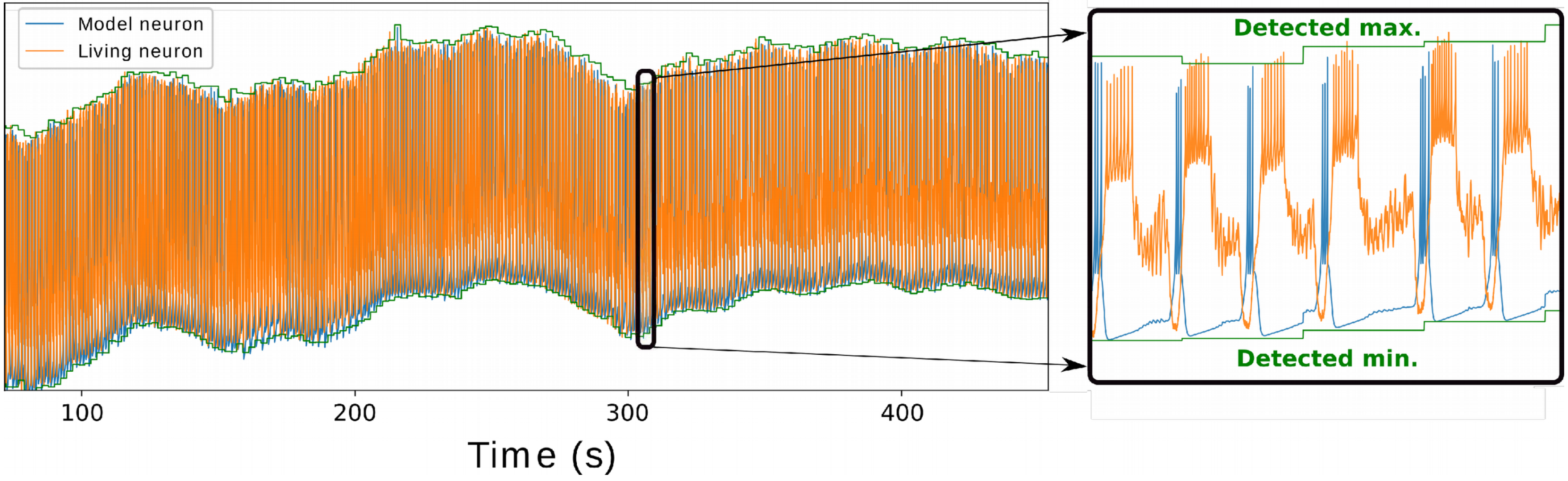
- **Time scale of the living neuron** (detected in real time) **and frequency of the interaction** (DAQ rate) **are taken into account** to adapt the neuron model (including integration step) to the same resolution and temporal scale as the living part.

- The amplitudes and **voltages are scaled in real time** before the communication signals are sent. Thus, **each neuron works in its own dynamic regime** while sustaining the bidirectional communication.



Online adaptations

- During the experiment the **conditions can change: e.g. offset, drift, etc.**
- For this reason **the interaction is monitored** in real time to ensure that all conversion factors are updated.
- If a change is detected the **system dynamically adapts to it.**



Experimental recording with drift compensation

Hybrid circuits automation algorithms

Automation algorithm	Input parameters	Advantages/Use cases
Temporal Scaling	Model integration or interpolation step, sampling rate	Same timing for living and model neurons, temporal precision
Amplitude Scaling	Working range of living/model neurons, asymmetry constants	Longer experimental life, realistic interactions
Drift Compensation	Online living neuron intracellular or extracellular voltage measures	Compensate electrode problems, intrinsic modulations
Synaptic Tuning/Calibration	Synapse parameters and time constants	Effective currents
Model Tuning/Calibration	Model parameters	Specific experiment adaptation, model autocalibration
Automatic Activity Control	Synapse and model parameters, stimulus parameters and time constants	Realistic/natural dynamics
Automatic Mapping		Revealing dynamics and bifurcations and characterization as a function of the hybrid circuit parameters

Hybrid circuits automation algorithms

<table>
<tr><th>Automation algorithm</th><th>Event detected</th><th>Performance measures</th></tr>
<tr><td>Temporal Scaling</td><td>Spikes, bursts, hyperpolarization intervals, etc.</td><td>Event timings, periods, synchronization levels, target phases</td></tr>
<tr><td>Amplitude Scaling</td><td rowspan="2">Max. and min. voltage values</td><td>Working range assessment</td></tr>
<tr><td>Drift Compensation</td><td>Dynamic range assessment</td></tr>
<tr><td>Synaptic Tuning/Calibration</td><td rowspan="4">Pre and post synaptic voltage, number and temporal structure of spikes, current ranges, hyperpolarization times, burst duration, phases, etc.</td><td rowspan="4">Synchronization, regularization level, rhythm properties, intervals and phases</td></tr>
<tr><td>Model Tuning/Calibration</td></tr>
<tr><td>Automatic Activity Control</td></tr>
<tr><td>Automatic Mapping</td></tr>
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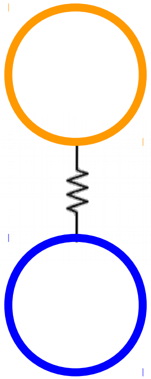
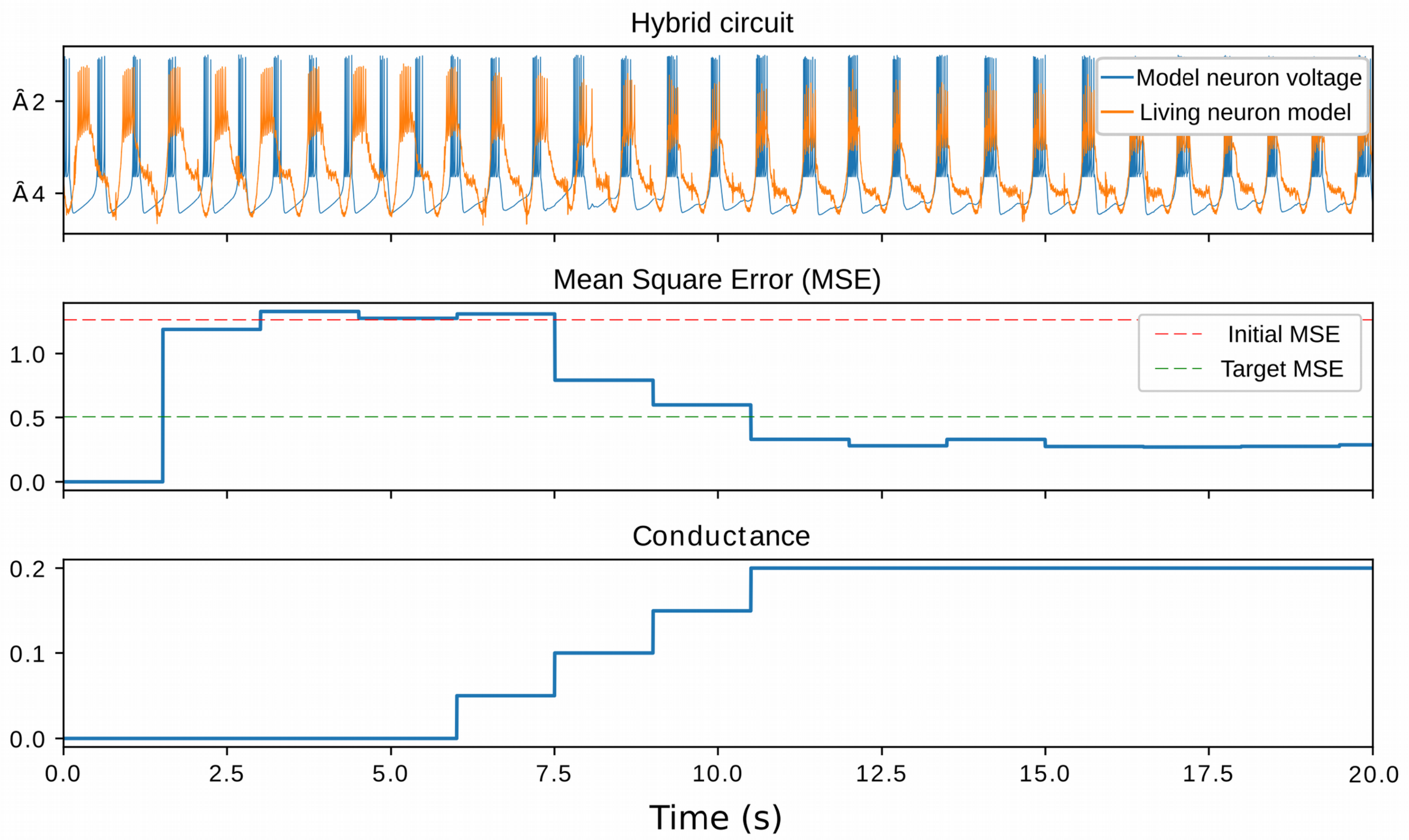
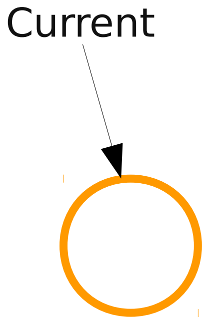
Closed-loop validation experiments

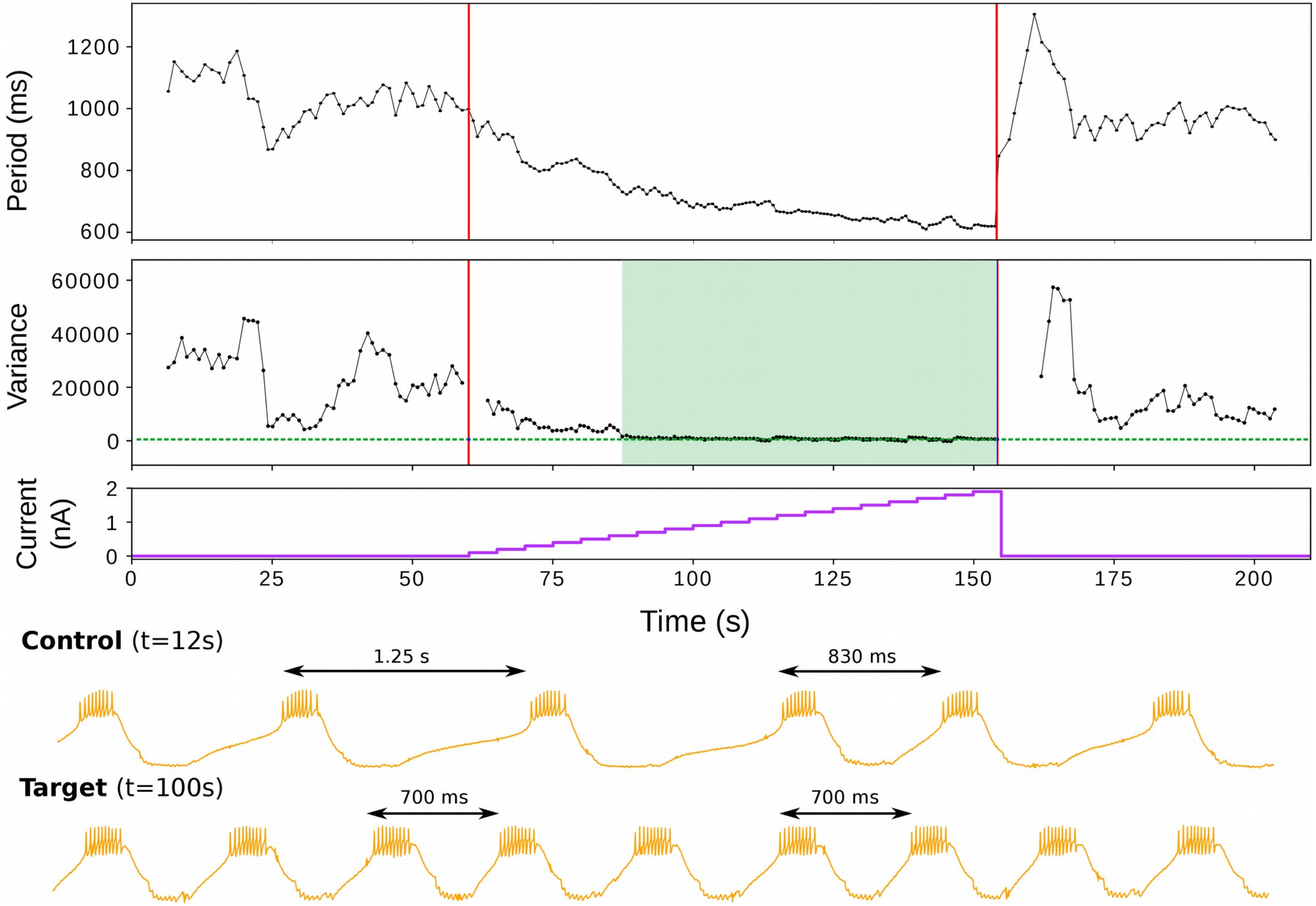
- Synchronization goal driven by online Mean Square Error metrics





Regularization by goal-driven current injection

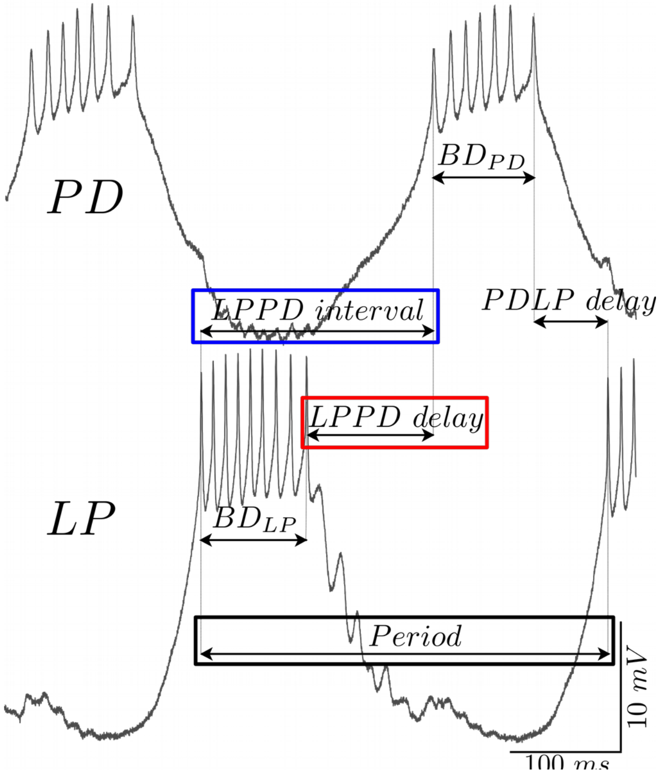




Unveiling hidden dynamics

- A dynamical invariant is a relation between temporal intervals that is preserved in a cycle-by-cycle manner, even **during transients**.

- Example: the interval defined by the beginning of the bursting activity between the two neurons and the instantaneous period of the sequence.



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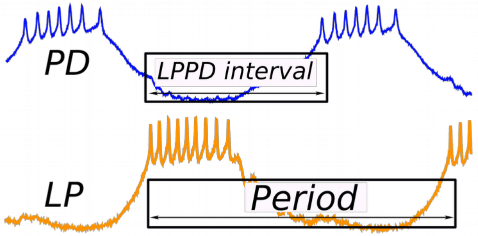
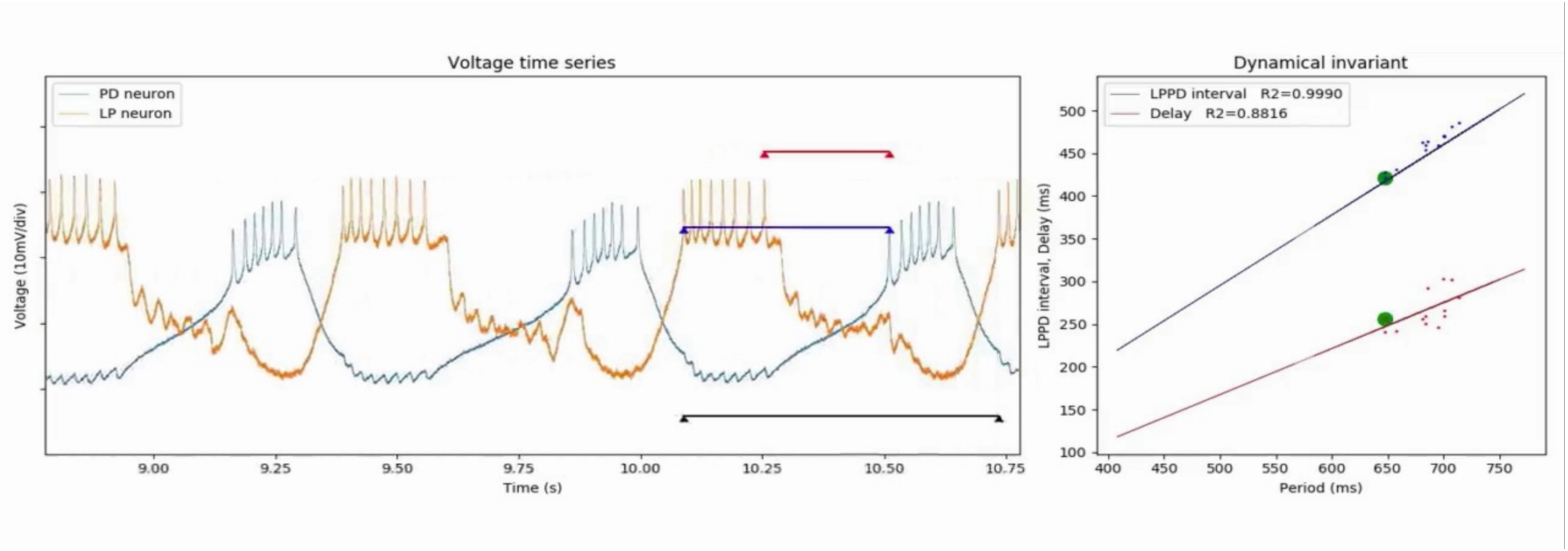
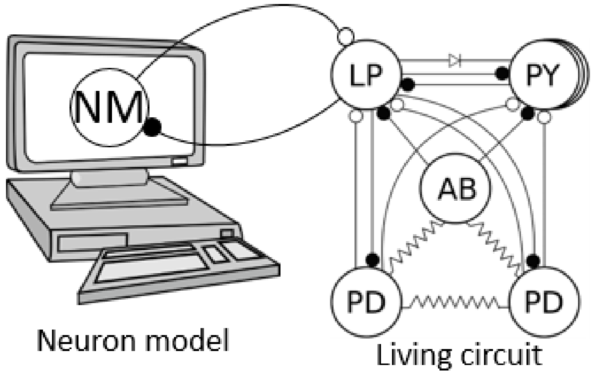
Unveiling hidden dynamics

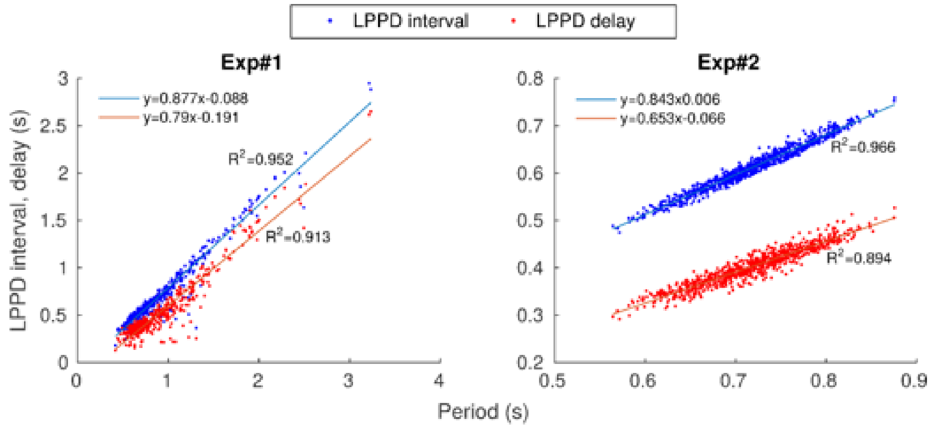




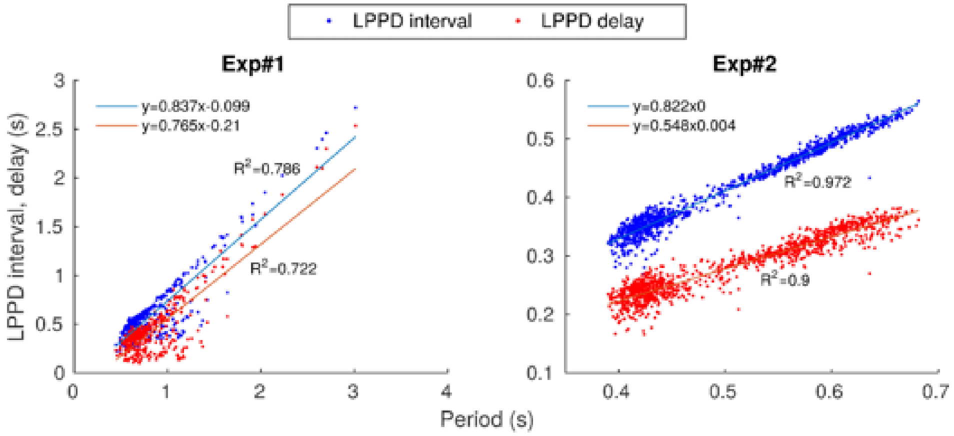
Dynamical invariants in hybrid circuits

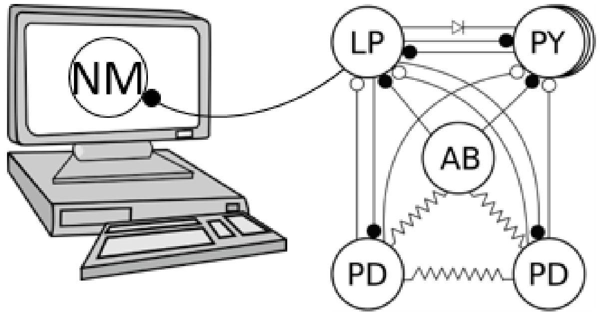
- **Bidirectional chemical synapse**





- **Monodirectional fast chemical synapse from LP to neuron model**

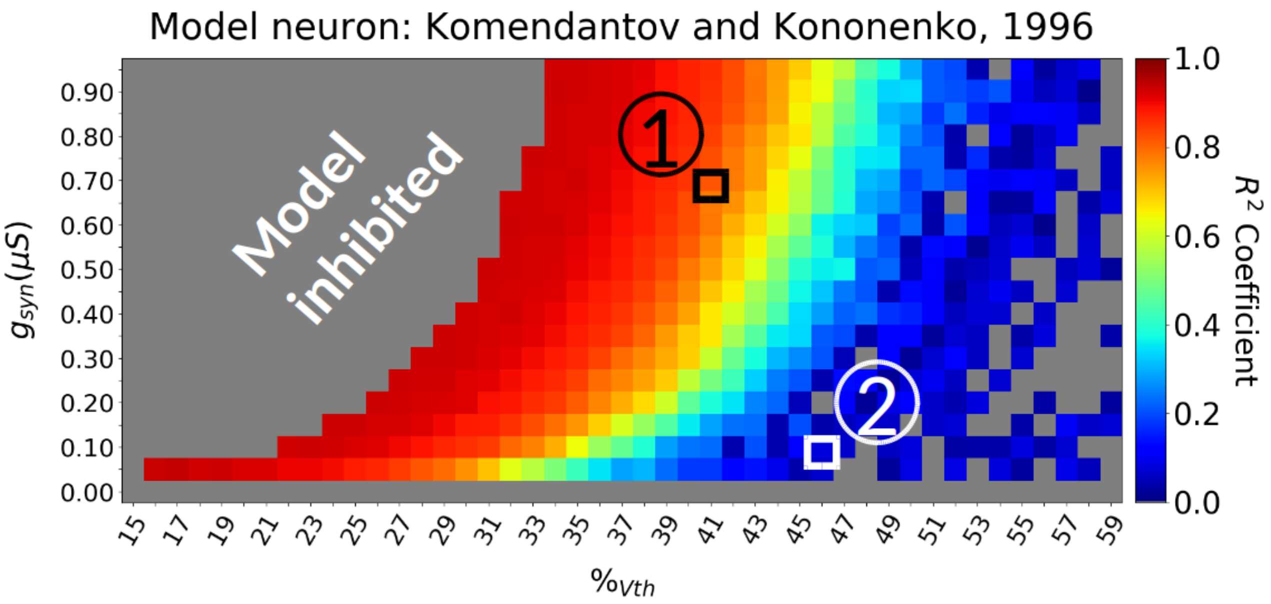


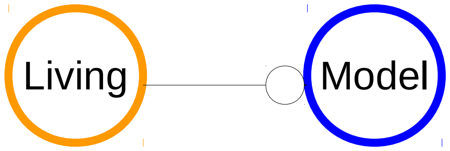


Mapping dynamics

- Despite hand tunning can work, is a time consuming process, led by trials and errors
- Despite this, we map automatically different configurations (changing the parameters that define the model and synapse behavior)
- This can be do it online during the experiment, testing some configurations. But in our case can take up to three minutes for each configuration
- To massively test how a parameters affects the appearance of the invariant, we use a mono-directional configuration, allowing us to test hundreds of configurations in less than a hour

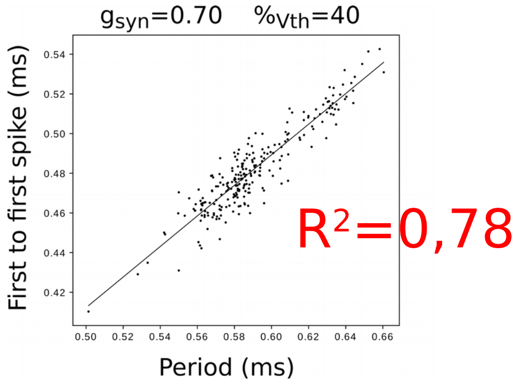
Mapping dynamical invariants



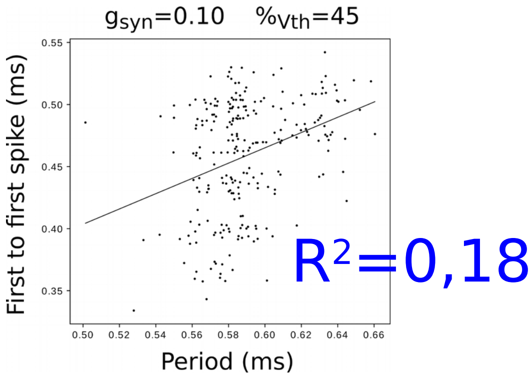


Monodirectional chemical synapse

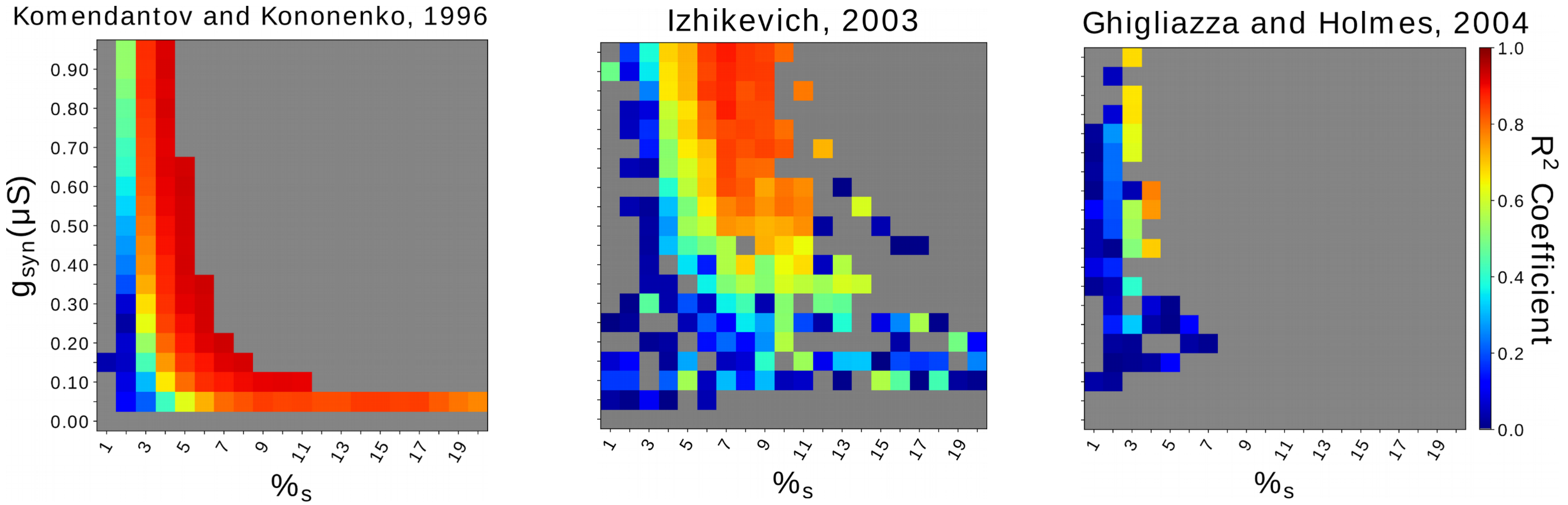
1. Antiphase with invariant



2. Antiphase with no invariant



Mapping dynamical invariants



- This exploration allows to compare how different neuron models react to the same hybrid circuit configuration and can help to determine which model dynamics and parameters can generate dynamical invariants.

Discussion

- **Closed-loop protocols** with the nervous system **require experiment-specific adaptations** to work properly:

  - The **parameters** of the implementation **must be evaluated** for each preparation.
  - Some **parameters can be adapted during the experiment** to archive better results.

- **There is a need for algorithms** and closed-loop paradigms **that automatically address** these adaptations**:**

  - Can be used to **control or tune the behavior of the living circuit** in an automated manner.
  - Can be used to **automatically map the parameter space to achieve a given goal** and in general to **explore and map circuit dynamics.**

Discussion

- **Automatic adaptations** to/from the living system **expand the life expectancy** of the preparations.
- **Select manually the models parameters is not a trivial task** that have to be carefully addressed.
- In our case, the results show that **mapping graded synapse parameters in hybrid circuits is an effective way to explore and reproduce** living neuron **dynamics**.

GNB Team

Irene Elices
Rodrigo Amaducci
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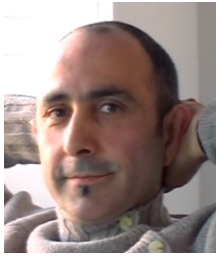
Francisco B. Rodríguez
Pablo Varona





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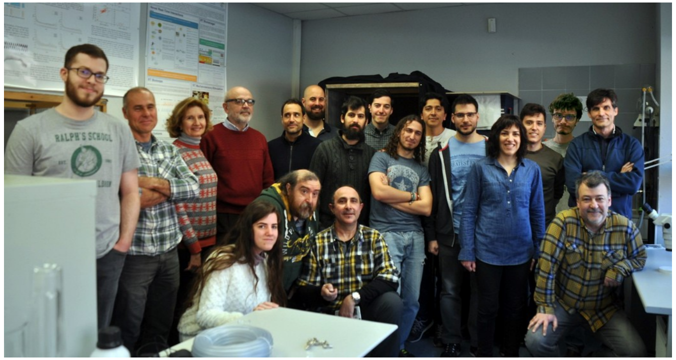
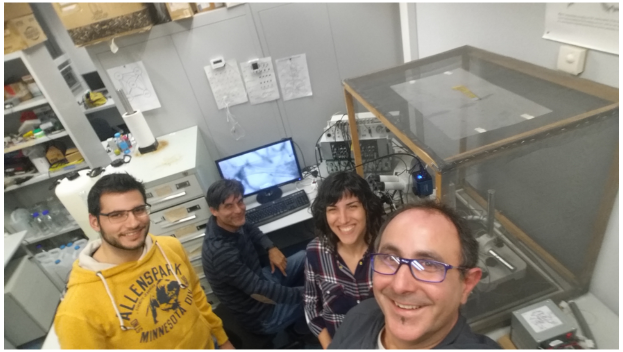

Thank you!

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P206: Parameter exploration in neuron and synapse models driven by stimuli from living neuron recordings

Sunday, July 19 • 9:00pm Central European Time

P207: Hybrid robot driven by a closed-loop interaction with a living central pattern generator with online feedback

Sunday, July 19 • 9:00pm Central European Time

O11: Experimental and computational characterization of interval variability in the sequential activity of the Lymnaea feeding CPG

Monday, July 20 • 5:00pm Central European Time

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Amaducci, R., Reyes-Sanchez, M., Elices, I., Rodriguez, F.B., & Varona, P. (2019). RTHybrid: a standardized and open-source real-time software model library for experimental neuroscience. Frontiers in Neuroinformatics, 13, 11. https://doi.org/10.3389/fninf.2019.00011

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