Estimating parameters of biological neuronal networks using Convolutional Neural Networks

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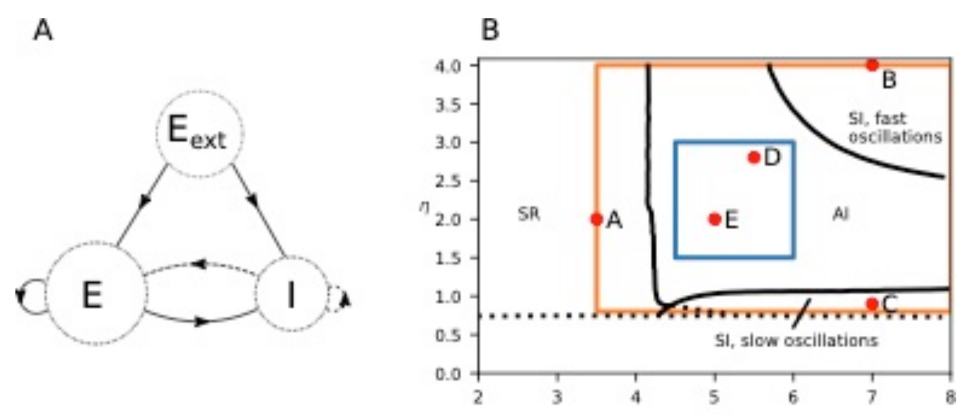
Motivation

- Realistic neuronal models grow in size due to increase in computer power, and we may soon see networks similarly sized to human brain networks (~10^{10} neurons)
- Local field potentials (LFP) are an experimentally accessible electrophysiological measure of collective neuronal activity in vicinity of the recording electrode
- It is unclear what information about the neuronal network is available in the LFP, but this is critical when it comes to constraining neuronal models based on experiments
- Here we demonstrated that CNNs can accurately identify parameters of the neuronal network model from the corresponding LFP output

The Brunel model

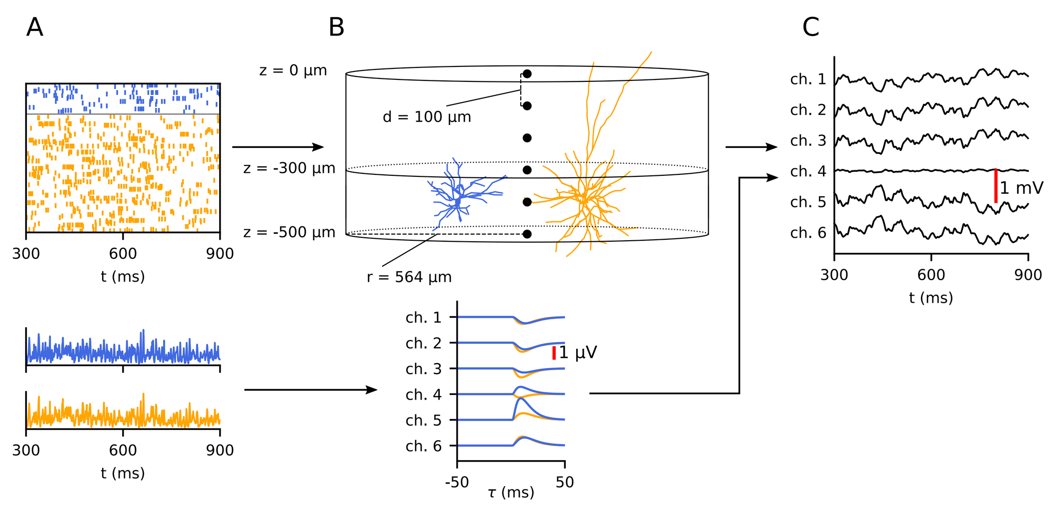
- Two-population model of 12'500 leaky integrate and fire neurons [1]
- Represents a small, randomly connected brain network
- Network can be parameterized by three variables:
  - Excitatory connection strength *J*
  - Relative inhibitory connection strength *g*
  - Strength of external input *η*



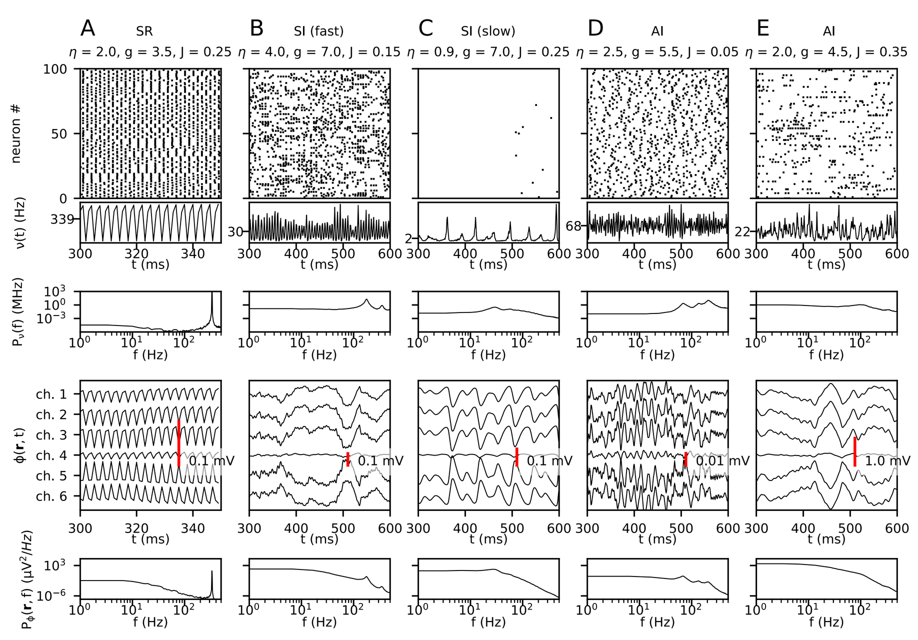
Brunel network model (A) and phase diagram (B), orange and blue box indicate extent of two data sets, red dots indicate selected network states, states D and E similar to experimental brain recordings

Simulation

- First, we use a point-neuron network to simulate the network activity
- Then, detailed multicompartment neuron models are used to compute the extracellular potential (LFP) [2]



Overview of the hybrid LFP approach [2]: Colum A shows the model network activity with spiking (top) and population firing rate (bottom), column B the morphology of each neuron class (top) and the mapping of population activity on channels (bottom). Column C shows the simulated LFP as recorded with six simulated electrodes

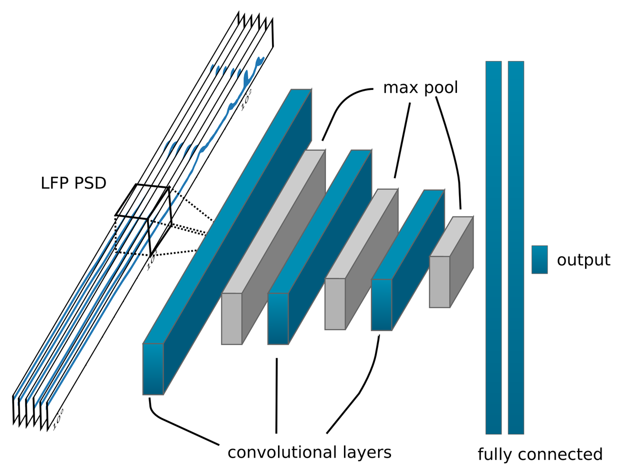


Example network states of the Brunel model with spike raster plot, firing rate, LFP and LFP PSD, A synchronous regular state, B and C synchronous irregular state, D asynchronous irregular state and E asynchronous irregular state

CNN architecture

- Estimate parameters *J*, *g*, and *η* across different network states
- Simulation output is stationary, we therefore use LFP power spectrum as input
- Utilize CNNs to benefit from automated feature extraction [3]
- 40'000 training samples and 10'000 test samples
- Adam optimizer, mean square error loss
- Implementation in Keras with Tensorflow backend [4]

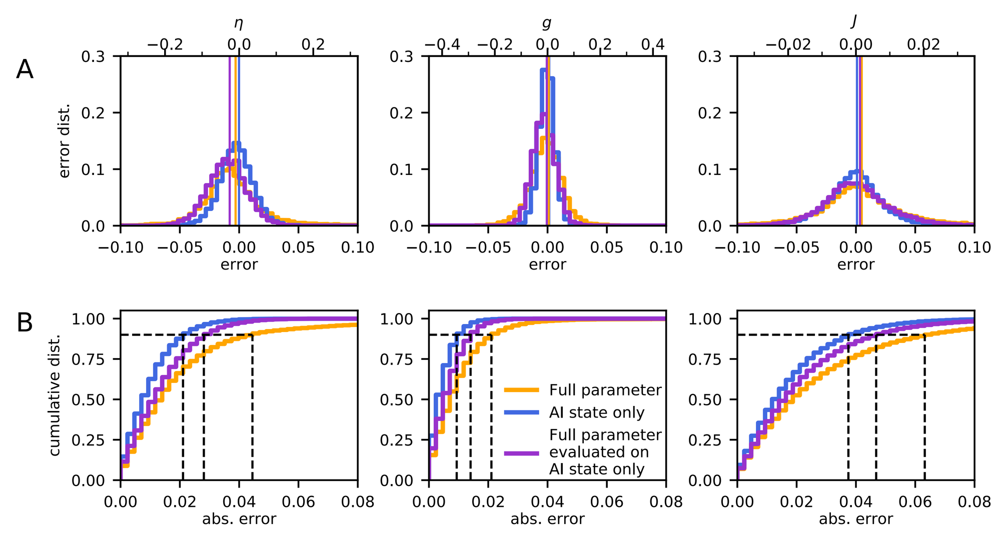
Layer	Params
Conv. layer 1	kernel size: 12x6x20 activation: ReLU
Max pool 1	window size: 2 stride: 2
Conv. layer 2	kernel size: 3x20x20 activation: ReLU
Max pool 2	window size: 2
Conv. layer 3	kernel size: 3x20x20 activation: ReLU
Max pool 3	window size: 2
Dense layer 1	nodes: 128 activation: ReLU
Dense layer 2	nodes: 128 activation: ReLU
Output layer	nodes: 3 activation: None



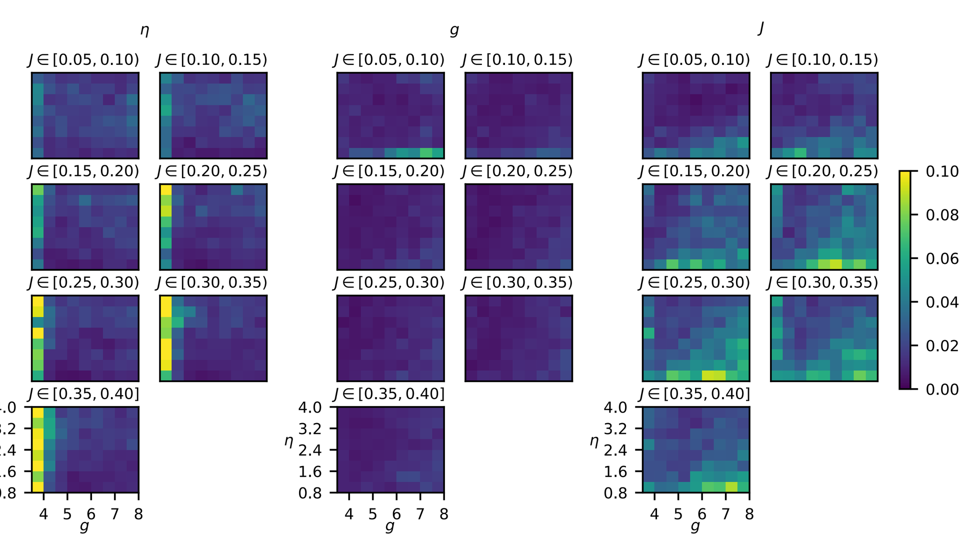
Sketch and details of CNN architecture used in this analysis

Results

- CNNs can accurately predict the network parameters *J*, *g*, and *η*
- A high estimation accuracy is achieved for all parameters (<5%)
- The errors are near bias-free
- Parameter estimation accuracy varies over parameter space and network states



Estimation error of network parameters over the entire parameter space



Mean absolute parameter estimation error in different regions of the parameter space, the asynchronous irregular states is predicted with the largest accuracy

Conclusion

- CNNs were successfully used to extract biophysical network properties from the LFP for the first time
- Result shows that the parameters of the neural network are reflected in the LFP
- Will be extended to more complex models and non-stationary network activity
- Promising new data analysis tool for computational neuroscience
- Paper in preparation

References

- [1] Brunel, 2000, 2018, J Comput Neurosci 8, 183-208
- [2] Hagen et al., 2016, Cerebral cortex 26, 4461-4496
- [3] Rawat and Wang, 2017, Neural computation 29, 1252-2449
- [4] Collet et al., 2015, https://keras.io.

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