One size does not fit all: calibrating microstimulation to individual subjects using spiking network models

Cliff C. Kerr[1,2], John S. Choi[1], Salvador Dura-Bernal[1], Joseph T. Francis[1], William W. Lytton[1,3]

[1] SUNY Downstate, Brooklyn, NY; [2] University of Sydney, Australia; [3] Kings County Hospital, Brooklyn, NY

1. Introduction

Microstimulation is a powerful tool for manipulating brain activity, but its drawbacks are sobering: electrode efficacy is variable, the cells being stimulated are rarely those being recorded from, and the number of independent electrodes is much smaller than the dimensionality of the systems being stimulated. In this pilot study, we show how a spiking network model can be used with optimal control to expedite the development of microstimulation protocols.

2. Neural data & model

Data were recorded from the somatosensory cortices of four anesthetized rats, with intrathalamic microstimulation as well as tactile stimulation (Fig. 1). The simulation (Figs. 2–3) consisted of 2000 spiking Izhikevich neurons [1] representing cortex and thalamus, with connectivities drawn from empirical data [2].

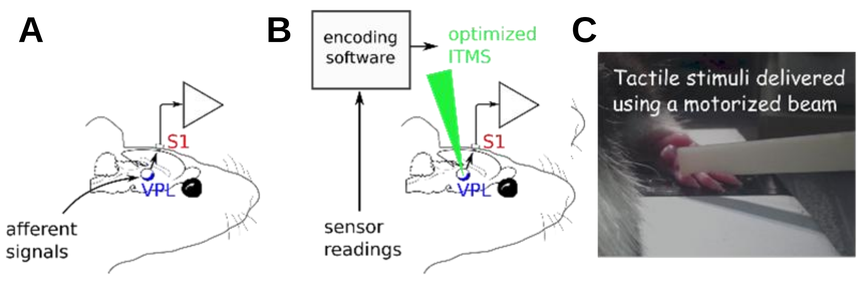

Fig. 1: **(A)** Natural flow of sensory information. **(B)** Sensation replaced by direct thalamic microstimulation. **(C)** Mechanical actuator delivering tactile stimuli.

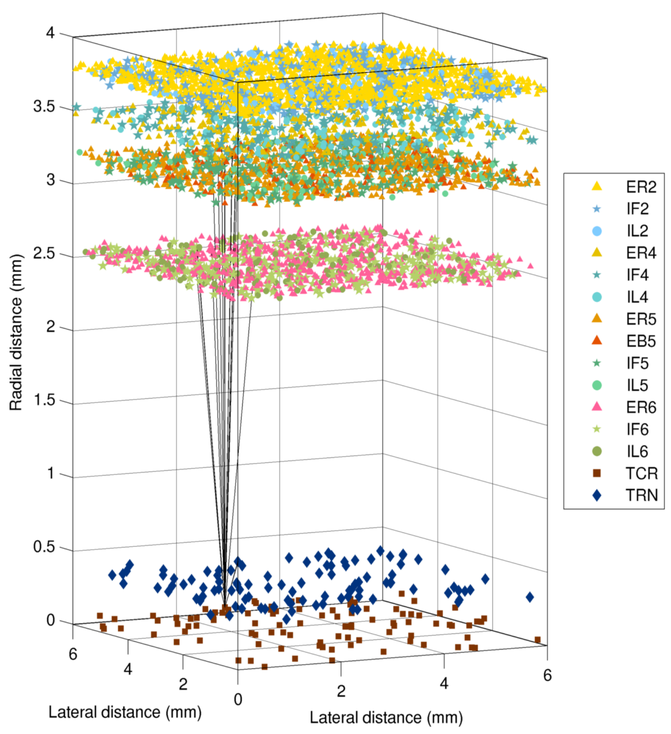

Fig. 2: Layout of the model. The 28 efferent connections from a single thalamocortical relay neuron are shown (black lines).

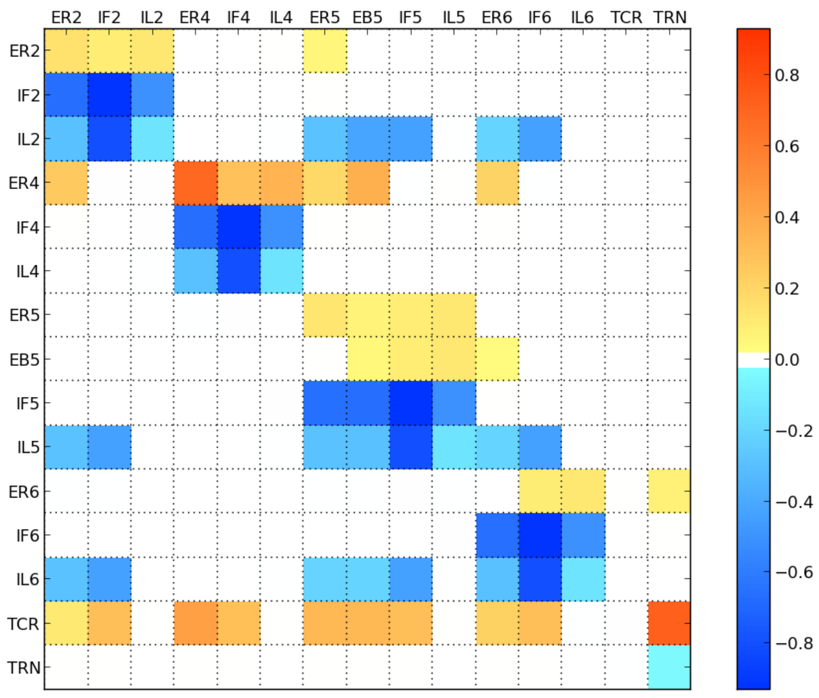

Fig. 3: Connectivity of the model, showing effective connectivity from rows to columns. Red = excitation, blue = inhibition; number = layer; **E** = excitatory; **I** = inhibitory; **R** = regular firing; **B** = bursting; **F** = fast-spiking; **L** = low-threshold spiking; **TCR** = thalamocortical relay; **TRN** = thalamic reticular nucleus.

3. Optimization

- Optimization was performed using Bayesian adaptive locally linear stochastic descent (BALLSD): for an objective function $E = f(\mathbf{x})$, BALLSD varies a random parameter i and evaluates $E_k^{\pm} = f(\mathbf{x} \pm \delta(i))$.
- If this step is an improvement, then BALLSD (1) accepts the new parameter, (2) increases the probability of selecting this parameter in future, and (3) increases the step size.
- Connection weights, stimulation amplitude, and background input rate were optimized.

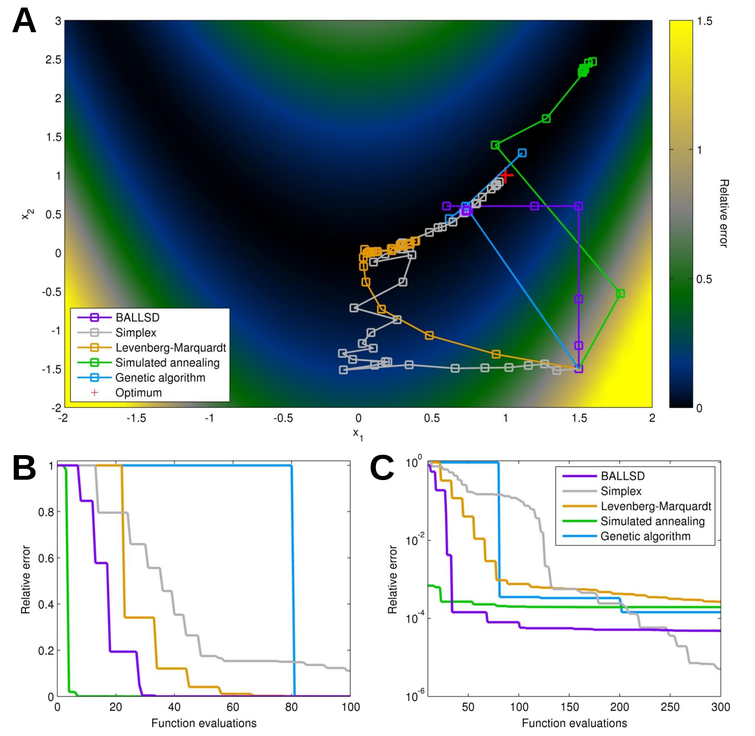

Fig. 4: Example of BALLSD. **(A)** Trajectories of BALLSD vs. traditional algorithms. Note the locally linear steps of BALLSD that rapidly adapt in size. **(B)** Relative error of each method, showing the initial stage of the algorithms. **(C)** Relative error for each method, showing the asymptotic stage of the algorithms.

4. Results

- The model was calibrated to the experimental firing rates and local field potential spectra of each rat using just 50 function evaluations, requiring approximately 80 min. of CPU time per subject (Fig. 5); 10 – 1000 more iterations would be required to achieve an optimal fit.
- Due to the efficiency of the linear model used with model predictive control (MPC), just 200 s of training data sufficient (Fig. 6).
- A controller that was trained on pooled or generic data had poor performance compared to one trained on individual rats (Fig. 7).

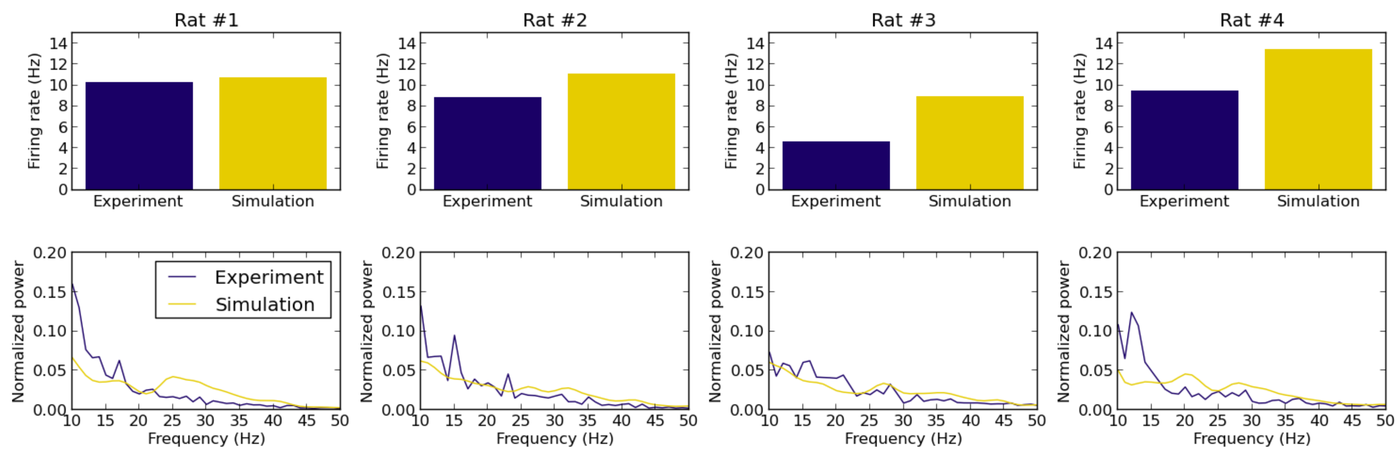

Fig. 5: Calibration of four different simulations to experimental data from four different rats using a small number of function evaluations. Calibrations are shown to firing rates (top) and local field potential spectra (bottom).

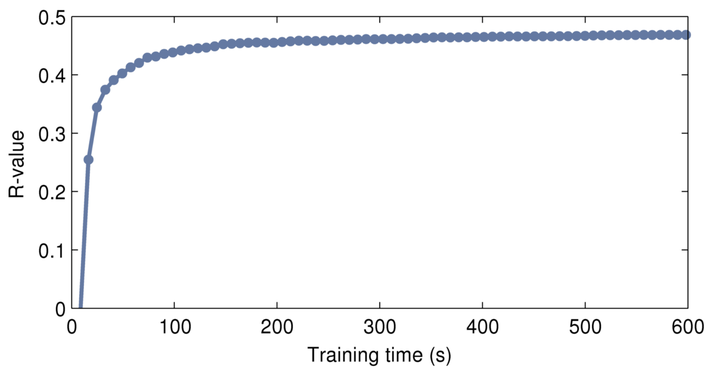

Fig. 6: Accuracy of MPC as a function of data length. While accuracy continues to increase up even after 600 s of data, 98% of the accuracy can be attained with just 200 s of data.

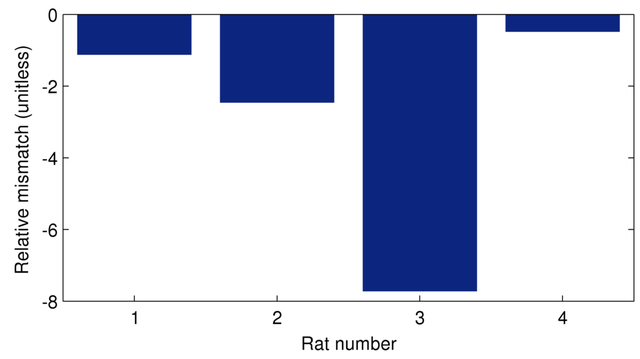

Fig. 7: Compared to MPC trained on a generic neural model the controller trained on rat-specific neural models had consistently greater accuracy when trained on individual-specific data.

5. Summary

- An adaptive descent algorithm was used to calibrate spiking network models to data from different rats.
- To our knowledge, this is the first time spiking network models have been used to investigate differences from tuned to individual rat brains.
- Even with a small number of function evaluations, MPC used with individually calibrated models had consistently better performance than MPC trained on a generic model only.
- Spiking network modeling may prove to be a useful tool in designing in vivo microstimulation protocols.

References

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Further information

E-mail: cliffk@neurosim.downstate.edu

Web: neurosimlab.org