GPUfit: A Tool for Real-Time Model Calibration and Prediction Testing

Richard Bertram

Department of Mathematics and Programs in Neuroscience and Molecular Biophysics Florida State University, Tallahassee, FL.

Funding: National Science Foundation DMS1220063

Duke University 2014





Maurizio Tomaiuolo (High Performance Computing Institute, Frederick, MD)

Five types of anterior pituitary endocrine cells

- 1. Lactotrophs: secrete prolactin
- 2. Somatotrophs: secrete growth hormone
- 3. Gonadotrophs: secrete luteinizing hormone and follicle stimulating hormone
- 4. Corticotrophs: secrete ACTH
- 5. Thyrotrophs: secrete thyroid stimulating hormone



Thanks to Arturo Gonzalez-Iglesias, Jose Arias-Cristanch, and Ruth Cristancho-Gordo Immunocytochemistry for prolactin, growth hormone, and leutinizing hormone.

Goal

Use mathematical modeling and analysis to help understand the electrical activity of the different types of endocrine pituitary cells



Van Goor et al., J. Neurosci., 2001:5902, 2001

What makes pituitary cells burst and secrete?



Equations

 $I_{noise=0}$

voltage
$$C\frac{dV}{dt} = -(I_{Ca} + I_{K} + I_{SK} + I_{BK} + I_{leak} + I_{noise}),$$

 I_{K} activation $\tau_{n}\frac{dn}{dt} = n_{\infty}(V) - n,$
 I_{BK} activation $\tau_{BK}\frac{df}{dt} = f_{\infty}(V) - f,$
cytosolic calcium $\frac{d[Ca]}{dt} = -f_{c}(\alpha I_{Ca} + k_{c}[Ca]),$

Ionic current have an Ohmic form, e.g., $I_k = g_k n(V - V_K)$

Conductance and time constants are all parameters. There are more parameters in the equilibrium functions.

Picking parameter values

If your model has many parameters, how do you find values for them all?



Heterogeneity...a big problem

The mix of ionic currents within a single cell type is highly variable



Electrical activity is highly variable, and

The "true" parameter values vary from cell to cell

Pituitary cells are very heterogeneous

The mix of ionic currents within a single cell type is highly variable, as shown with the GH4C1 cell line



Possible parameter distribution scenarios



+ = mean of distribution

Marder and Taylor, Nature Neurosci., 14:133, 2011

Averaging over distribution should be fine

Possible parameter distribution scenarios



+ = mean of distribution

Marder and Taylor, Nature Neurosci., 14:133, 2011

Averaging puts you out of the distribution

Possible parameter distribution scenarios



+ = mean of distribution

Marder and Taylor, Nature Neurosci., 14:133, 2011

Averaging puts you out of the distribution

Does heterogeneity matter for us?

One spiking model cell

Another spiking model cell

A third spiking model cell

Tomaiuolo et al., Biophys. J., 103:2021, 2012

Main approach: Parameterize the model to an individual cell

Parameterize the model to an individual cell, while still patched onto that cell. Then different cells will have different parameter vectors. Set parameters to fit <u>features</u> of the voltage trace, rather than the voltage trace itself

Feature fitness function

$$F_{features} = \sum_{j} c_{j} \exp\left(-\frac{(m_{j} - d_{j})^{2}}{\sigma_{j}}\right) / \sum_{j} c_{j}$$

F=fitness function m_j =model feature d_j =data feature c_j =feature weight σ_j =feature scaling

$$\left|m_{j}-d_{j}\right|$$

Also fit voltage clamp data

Maximize $F = \beta F_{features} + (1 - \beta) F_{clamp}$ where $\beta \in [0, 1]$

Optimization using a genetic algorithm

We need rapid calibration, so use a Programmable Graphics Processing Unit (GPU)

Cost < \$ 1000

Feature planes can be rapidly computed

100x100 grid 10,000 simulations Simulation time=70 sec each Total computation time=20 sec

Example: Calibrate, predict, and test

The model (red) is fit to a bursting Gh4 cell (black)

Feature plane for BK conductance and time constant

Model prediction tested by blocking BK current with paxillin

Actual cell (black) and model (red) convert from bursting to spiking

Feature plane for BK conductance and time constant

X Best fit to bursting data

Double BK time constant

The Dynamic Clamp: a tool for adding a model current to a real cell

Prediction tested by adding BK current via D-clamp, with τ_{BK} =10 ms

Black=cell Red=model

Adding BK current with slow activation converts bursting to spiking

Feature plane for BK conductance and time constant

X Best fit to bursting data

Increase BK conductance

Prediction tested by adding BK conductance to a bursting cell with D-clamp

Black=cell Red=model

Bursting persists, with more spikes per burst

Understand bursting using geometric singular perturbation analysis

$$\varepsilon V = f_1(V, n, f, Ca)$$

$$\cdot$$

$$n = f_2(V, n)$$

$$\cdot$$

$$f = f_3(V, f)$$

$$\cdot$$

$$Ca = f_4(V, Ca)$$

Analyze the reduced system obtained in the limit $\varepsilon \rightarrow 0$ Voltage V is in a state of quasi-equilibrium with the other variables

(Work done with Martin Wechselberger, Joël Tabak, Theo Vo, and Wondimu Teka)

Geometric singular perturbation theory tells us about the origin of bursts

The "spikes" of the bursts are small rotations of the burst trajectory that occur due to the presence of a **folded node singularity** in the slow subsystem.

Secondary . canards

Prediction: Reducing K(dr) conductance increases the burstiness

Diameter: active phase duration Color: number of spikes per active phase

Teka et al., J. Math. Neurosci., 1:12, 2011

Prediction tested using D-clamp

Control cell

Subtract some K(dr) current

Subtract more K(dr) current

Summary

Bertram et al., in press

The "traditional" approach

Our new approach

