Xolotl: An Intuitive and Approachable Neuron & Network Simulator in MATLAB

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An Intuitive Neuronal Simulator

ABSTRACT

xolotl is a free and open-source neuronal simulator written in C++ with MATLAB wrappers. Biophysically-detailed models of networks can be designed efficiently using an intuitive language tightly coupled to the object-based architecture of the underlying C++ code. Models can be specified by adding conductances to compartment objects. The structure is modular, serialized, and searchable, permitting high-level programmatic control over nearly all features of the models. C++ templates are provided for developing new conductances, compartments, and integration schemata. It also includes a customizable graphical user interface (GUI) for rapid prototyping and hand-tuning conductances in real-time. The modular structure and accessibility to all parameters, variables, and dynamics of the model network in MATLAB facilitate rapid construction and assessment of model networks. xolotl is freely available at https://github.com/marderlab/xolotl. This tool provides straightforward implementation and fast simulation of neuronal models while permitting full control over every aspect of the network and integration.

Keywords: simulator, MATLAB, C++, conductance-based, neuron, network, keyword

1 INTRODUCTION

xolotl (https://github.com/marderlab/xolotl) is a fast single-compartment and multi-compartment simulator in C++ with MATLAB wrappers. Written with an emphasis on ease-of-use, xolotl can simulate single-compartment conductance-based models, networks of these, and detailed multi-compartment models. xolotl exploits a novel automatic type system, cpplab, which binds MATLAB code to C++ header files, creating objects and classes *ad libitum* in MATLAB which reflect the underlying object-oriented code. xolotl implements cpplab to represent the nested structure of conductance-based models, and exploits the computational efficiency of the low-level programming language to quickly integrate models. For this reason, models can be implemented entirely in MATLAB with a few lines of code.

Models are specified in MATLAB by a nested structure. The xolotl object contains compartments which themselves contain conductances. Synapses belong to the xolotl object and connect compartments together. The high-level specification supports arbitrarily large network and multi-compartment morphologies.

The software has been implemented in MATLAB due to its ease-of-use and popularity among neuroscientists. cpplab provides a powerful backend for specifying and integrating models without relying on the significantly slower and limiting MATLAB codegen. While automated C++ transpiling from MATLAB using the proprietary codegen can drastically improve performance over loops through strong typing and memory pre-allocation, supervenience of MATLAB over C++ prevents efficient use of low-level features, such as passing by reference and object-oriented programming. Minimal experience with MATLAB is required to use xolotl, and all equations and integration methods are provided transparently to the end user. No string parsing of equations is required (Sherfey et al. 2018; Stimberg, D F M Goodman, et al. 2014; Stimberg, D F Goodman, et al. 2013)

xolotl comes packaged with visualization functions and a graphical user interface (GUI) for real-time manipulation of model parameters. Plotting of voltage, intracellular calcium, conductance gating functions, and time constants is provided by built-in xolotl methods. The GUI permits real-time tuning of any network parameters using numerical sliders in a graphical interface which displays the resultant membrane potential and intracellular calcium traces. The ease-of-use of these tools lends them to pedagogical applications and rapid exploration of toy models. This tool aims to simplify the investigation of dynamics of complex neural network models, facilitate collaborative modeling, and complement other tools being developed in the neuroinformatics community.

2 DESIGN GOALS

xolotl is designed to be easy-to-use without sacrificing speed.

The software has been designed in MATLAB due to its popularity among neuroscientists for pedagogy and research. xolotl capitalizes on MATLAB's straightforward structure array syntax to permit rapid prototyping and experimentation, especially for small neuronal networks of complex models. Parameters of conductances, neuronal compartments, and simulations may all be edited in the structure before any calls to integration functions. The underlying code is written in C++ for speed and memory optimization, and while models can indeed be integrated using the compiled binary, symbolic manipulations can be readily performed in MATLAB without ever touching the foundational code.

2.1 FEATURES

MATLAB provides a high level programmatic and graphical interface for implementing, manipulating, and visualizing models without sacrificing the enhancements of the underlying C++ code.

Modular structure. Models are specified by adding compartments and synapses to the xolotl object. Conductances are added to compartments and controllers can be added to conductances. This modular structure recapitulates the biophysics of the Hodgkin-Huxley formalism and obviates the need to explicitly write out equations, which in xolotl are contained within the conductance header files.

Interface between C++ and MATLAB. xolotl relies on cpplab constructions, which allow the user to exploit the efficiency of low-level C++ code. MATLAB treats cpplab objects as fully-typed variables allowing for symbolic manipulation using only the high-level programming language and graphical interfaces. xolotl is fast because all time-intensive code is written in C++. While automated C++ transpiling from MATLAB using the proprietary codegen can drastically improve performance over loops through strong typing and memory pre-allocation, supervenience of MATLAB over C++ prevents efficient use of low-level features, such as passing by reference and object-oriented programming. C++ provides speed improvements beyond the benefits of translating MATLAB features into low-level code. For this reason, cpplab has been designed to provide an interface for constructing, transpiling, and compiling C++ code to be called from within MATLAB. xolotl simulations are run entirely from C++ executables.

Automatic and efficient compiling. xolotl automatically handles transpiling and compiling MATLAB code into C++. The MD5 algorithm hashes the network to compile a new binary and MEX bridge file only if needed and to confirm that the correct binary fetched during execution.

2.2 SYNTAX

MATLAB can easily control the cpplab objects using the standard, flexible data structure notation popular in high-level scripting languages.

Adding features. The add function creates a compartment, conductance, or controller and affixes it as a field in the xolotl network structure. This function generates a MATLAB struct that faithfully represents the underlying C++ code. Compartments add to the xolotl object and conductances add to compartments. Specific properties can be specified using key-value pair arguments (e.g. Figure 1A).

Finding features. cpplab comes with several features which simplify the handling of complexly-nested models. The find function acquires a cell array of all properties of the network which satisfy a search condition. For example, one can find all paths to maximal conductances within the 'HH' compartment by:

```
x.find('HH*gbar');
```

To extract a vector of the maximal conductances:

```
gbars = x.get('HH*gbar');
```

To set the maximal conductances all at once:

```
x.set('HH*gbar', gbars)
```

Compartments. A model neuron consists of one or more compartments, each representing a section of membrane with capacitance and surface area. Isopotential models require one compartment, whereas models with multiple neurons, units, or non-trivial morphology require multiple compartments. All specifiable properties of compartments are shown in Supplementary Table 1.

Synapses. xolotl provides some features for generating complex models. Synapses can be added with the connect function. At minimum synapses possess identifiers to presynaptic and postsynaptic compartments and default to electrical synapses. All specifiable properties of synapses are shown in Supplementary Table 2. To create axons or transport chains, the slice function splits a compartment into *n* discrete segments and adds these compartments to the network connected by electrical synapses.

Conductances and controllers. All conductances contain fields for maximal conductance and reversal potential. Conductances with activation and inactivation variables include them as *m* and *h* respectively. Gating functions and their respective time constants are contained within the conductance header file. xolotl comes packaged with conductances from several dozen papers (Supplementary Table 3).

Creating custom cpplab objects. xolotl contains template header files for producing custom conductances. The template contains instructions on how to design novel conductances with arbitrary specifications.

Simulation. Models are simulated in `xolotl` with the `integrate` function which outputs as time series the membrane potentials, intracellular calcium concentrations, controller states, intrinsic currents, and synaptic currents. The `integrate` function also accepts an argument which specifies injected current or clamped voltage.

Numerical integration. `xolotl` uses the exponential Euler method for single compartment models, forward Euler for gating variables, and a Crank-Nicholson regime for electrically-coupled compartments (Butcher 2016; Dayan and Abbott 2001; Oh and French 2006) These defaults provide a mix of speed, accuracy, and stability, and are built into the `cpplab` header files. Custom `cpplab` header files can be customized with any iterative integration method. The simulation time-resolution can be specified to target arbitrary precision, and an output time step can be selected to support automatic down-sampling for memory considerations.

'Closed-loop' vs. 'open-loop.' Simulations can be run in 'closed-loop' mode where each simulation begins by resetting all dynamical variables to their initial conditions at instantiation, or 'open-loop' mode which begins simulation with the current network state.

Using the graphical interface to manipulate parameters. `xolotl` comes packaged with a graphical user interface for visualizing parameter changes in real-time. The `manipulate` function opens the GUI, which displays a figure plotting the membrane potential and intracellular calcium concentration of all compartments as time series, and a dialog box with customizable sliders for all parameters of the model, much like the `Manipulate` function in Wolfram `Mathematica`. Moving the sliders integrates the model in 'open-loop' mode with the new parameters. The parameters available in the sliders can be customized by passing a cell array to manipulate. For example, to only see sliders for maximal conductances of the `HH` compartment, call `x.manipulate('HH*gbar')`. Closing the GUI saves the network state of the model to the `xolotl` object. This is particularly helpful for rapid prototyping of models.

Optimizing parameters. `xolotl` can use the Global Optimization toolbox for `MATLAB` to optimize any accessible `xolotl` parameters. The toolbox is algorithm-agnostic and accepts any function in `MATLAB` with a scalar first output as the objective function. Simulations run on multi-core processors or high-performance computing clusters using the Parallel Computing toolbox.

2.3 LIMITATIONS

The focus on ease-of-use and speed means some features were elided in the streamlining process.

Reliance on compiled `C++` code. While `MATLAB` comes with robust features for compiling `C` and `C++` code, `xolotl` cannot run without `C++` compilation. For users, this necessitates the additional step of setting up the `mex` compiler which can be problematical, especially for nonstandard (e.g. Arch-based Linux). Secondly, compilation adds a small amount to total processing time. Longer simulations (>1000 time-steps) minimizes this effect. Adding new conductances also requires writing some `C++` code. For model conductances in the Hodgkin-Huxley formalism (Dayan and Abbott 2001; Hodgkin, Huxley, and Katz 1952) adjustments consist of changing default values in a template `C++` header file. Implementing a new integration scheme requires much more in-depth usage of `C++`.

Limited to conductance-based models. `xolotl` has been developed specifically for conductance-based models. It does not currently support rate- or current-based models.

Limited numerical integration strategies. While the exponential Euler method performs well in neuronal models (Dayan and Abbott 2001; Oh and French 2006) it may be desirable to use other methods under certain conditions. `xolotl` does not currently support other integration schemes for its built-in conductances, nor does the software support error-sensitive variable step-sizes 'out-of-the-box.'

Inefficient tools for handling large networks. While `xolotl` can integrate large networks (> 1000 compartments), `xolotl` uses string-based comprehension for labeling compartments which is suited to descriptive naming, but prohibits vector operations over compartments.

3 USAGE EXAMPLES

In `MATLAB`, users create a `xolotl` object and populate it with `cpplab`-generated objects which describe compartments, conductances, synapses, and controllers. The model is integrated with the `integrate` function where the membrane potential, intracellular calcium concentration, controller states, intrinsic currents, and synaptic currents can be outputs.

`xolotl` comes packaged with a library of pre-existing conductance and synapse objects which greatly simplify the task of constructing model neurons. These objects can be referenced by name and added directly to a compartment. Novel conductance dynamics can be easily written by modifying a template header file contained in the `xolotl` distribution, or designed entirely from scratch.

3.1 SIMULATING A HODGKIN-HUXLEY MODEL

The seminal Hodgkin-Huxley model of action potentials in the squid giant axon (Hodgkin and Huxley 1952; Hodgkin, Huxley, and Katz 1952) contains a fast inactivating sodium conductance (`NaV`), a non-inactivating delayed rectifier (`Kd`), and a passive leak current (Figure 1A). A compartment, `HH`, with membrane capacitance (`Cm`) and surface area (`A`) can be specified by Figure 1B. Network properties can be set during construction or afterwards using dot-notation in `MATLAB` (e.g. `x.HH.Cm`). Figure 1C shows the `MATLAB` command prompt after invoking the `xolotl` object `x`, displaying the hierarchical structure inherent in conductance-based treatments of neurodynamics.

This model was constructed using conductances from Liu et al. 1998 based on electrophysiological recordings from the lobster stomatogastric ganglion (Turrigiano, LeMasson, and Marder 1995) In the absence of applied positive current, the model is quiescent. When 0.2 nA is injected, the model tonically spikes (Figure 1D). The `integrate` function takes the applied current as an argument (e.g. `x.integrate(Iapp)`), so that the `xolotl` object is agnostic to integration-specific perturbations. The `plot` function generates voltage and intracellular calcium traces, where the voltage trace is colored by the dominant current. If the membrane potential is increasing, the strongest instantaneous inward current colors the trace. Conversely, if the membrane potential is decreasing, the strongest outward current colors the trace instead. Figure 1F-I display the results of the `show` function. Activation and inactivation steady-states and the voltage-dependent time constants of these gating variables describe the conductance dynamics in absence of other channel types.

3.2 PERFORMING A VOLTAGE CLAMP EXPERIMENT *IN-SILICO*

`xolotl` can recapitulate the results of voltage clamp experiments (Destexhe and Bal 2009; Swensen and Marder 2000, 2001; Turrigiano, LeMasson, and Marder 1995) Figure Figure 2 displays steps in the procedure to clamp the membrane potential of a cell with delayed rectifier potassium conductance. During an *in-vitro* experiment, confounding currents would be pharmacologically-blocked and two-electrode voltage clamp used to record tail currents at fixed membrane potential (Connor and Stevens 1971a,b)

A single-compartment model with a delayed-rectifier conductance is simulated at stepped membrane potentials. The model is simulated using the `integrate` function. The second argument determines the clamped voltage and the fourth output is the current trace.

```
[V, Ca, ~, I] = x.integrate([], clamped_voltage)
```

Currents under voltage clamp approach the steady-state holding current (Figure 2D-E). The current-voltage relation is the steady-state current over the clamped voltage, and the effective conductance is the derivative of that relation (Figure 2F-G). Since the effective conductance is the product of the maximal conductance and the gating variables (Dayan and Abbott 2001; Turrigiano, LeMasson, and Marder 1995) and the tail current is monotonically-increasing with time under voltage clamp, the current can be represented as non-inactivating. Fitting a sigmoid to various powers yields a model for the current dynamics (Figure 2H-I). These figures describe graphically the theoretical underpinnings of current analysis through voltage clamp and can serve as an effective pedagogical tool for computational and quantitative neuroscience.

3.3 SIMULATING NETWORK MODELS

Network models in `xolotl` consist of compartment objects connected by synapses. Synapses are stored in a vector array as a field of the `xolotl` object in `MATLAB`. Presynaptic and postsynaptic labels indicate the connectivity of the synapse. Figure Figure 3 implements a model of the triphasic pyloric rhythm in the stomatogastric ganglion of crustaceans. The pyloric model contains three compartments and seven synapses (Figure 3A). This structure is reciprocated in the hierarchy of the `xolotl` object, where conductances are contained within compartments (Figure 3B).

Representing the network in `xolotl` requires constructing three compartments and eight conductances in each using the `add` function.

```
x.add('AB', 'compartment', 'Cm', 10, 'A', 0.628, ...)
x.AB.add('prinz/NaV', 'gbar', 1000, 'E', 50)
...
```

Synapses are upper-level properties of the network which point between two compartments (Figure 3C). This exploits vectorized operations in `MATLAB` and does not require each synapse to possess a unique name. The `connect` function adds synapses to the network.

```
x.connect('AB', 'LP', 'Chol', 'gbar', 30)
```

3.4 SIMULATING INTEGRAL CONTROL

`xolotl` can implement homeostatic tuning rules as integral control. The controller computes an error signal (typically a function of intracellular calcium concentration), and adjusts the conductance or synapse it controls accordingly (O'Leary et al. 2013) In `xolotl`, integral controllers are `cpplab` objects added to the conductance or synapse they regulate.

In a demonstration adapted from O'Leary et al. 2013, integral control changes maximal conductances to bring a neuron from quiescence into a bursting regime. Calcium sensors supervene on maximal conductance density (Figure 4) to change neuronal activity. Each conductance in the `xolotl` structure contains a calcium-sensitive controller (Figure 4B-C). Maximal conductances increase from random initial conditions to a set which elicits the desired network output by minimizing the error signal (Figure 4D-F).

4 BENCHMARKS

To assess speed and accuracy, `xolotl`, `DynaSim` (Sherfey et al. 2018) and `NEURON` (Hines and Carnevale 1997) were compared in simulations over varied time resolution, simulation time, and number of compartments (Figure 5).

Single-compartment Hodgkin-Huxley-like models were generated using conductance dynamics from Liu et al. 1998 in the simulation environments. `xolotl` uses the exponential Euler method for integrating membrane potential (Dayan and Abbott 2001) `DynaSim` was implemented with a 2nd-order Runge-Kutta integration scheme as recommended for high-performance in the documentation. `NEURON` used an implicit Euler regime (Hines and Carnevale 1997)

To compare the integration methods, models were simulated for 5 s at varying time-resolution (Figure 5A). The ratio between 'simulated' time and actual runtime was defined as the speed factor. Higher values indicate faster simulations. The coincidence factor determines the correlative overlap between two spike trains (Jolivet et al. 2008) To assess accuracy over decreasing time-resolution for the three simulation environments, spike trains at each resolution were compared to a 'canonical' spike train (exponential Euler at a time-step of $dt = 0.001$ ms).

To assess the performance of the models in absence of set-up overhead, models were simulated with a time-resolution of 0.1 ms over increasing simulation time (Figure 5B). The speed factor was defined as the ratio between time represented in the simulation and actual runtime (simulation-time). Therefore, the speed factor represents how many times faster the simulation is than a real-time observation.

Many simulators perform well in simulations of many compartments (Brette et al. 2007; Delorme and Thorpe 2003; Sherfey et al. 2018; Vitay, Dinkelbach, and Hamker 2015)

`xolotl` and `DynaSim` performed with comparable accuracy at high time-resolution. At low time-resolution, `xolotl` significantly outperforms `DynaSim` in both accuracy and speed.

To test whether transient overhead effects had a significant effect on performance, `xolotl` and `DynaSim` were tested with time-step $dt = 0.1$ ms for varied lengths of time. `xolotl` and `DynaSim` both performed best during longer simulations, approaching maximal performance at $> 10^5$ time steps. `xolotl` is about 20 times faster for short simulation times and 3.5 times faster for arbitrarily large ones.

5 DISCUSSION

5.1 REPRODUCIBILITY

`xolotl` fosters reproducibility in science. While the availability of hosting sites with version control (viz. GitHub (`https://github.com`), GitLab (`https://gitlab.com/`), and Open Science Framework (`https://osf.io/`)) and the push for reproducibility in computational science (Baker 2016; Eklund, Nichols, and Knutsson 2016; Stodden et al. 2016) has resulted in the availability of source code, much of this code base is bespoke and difficult to implement (Sedano 2016; W Xu, D Xu, and Deng 2017)

To this end, `xolotl` provides an environment with readability and reproducibility in mind. Each network is hashed to provide a unique alphanumeric identifier. Conductance header files are easily viewed in the `xolotl` source files; conductances in `MATLAB` contain links to the full path of the generating file.

5.2 CIRCUMVENTING LANGUAGE TRADEOFFS

Executing `C/C++` code in higher-level languages such as `MATLAB` or `Python` often provides speed improvements for iterative code in algorithms.

`C` is statically-typed, with procedural syntax that provides low-level access to memory (Kernighan and Ritchie 1978) providing significant advantages for time-intensive computations. Unfortunately, automatic code-generation is limited by the supervening language. `MATLAB`, for instance, cannot use pointers or pass by reference, which limits the efficiency of `C` code automatically generated from `MATLAB`. Conversely, custom `C/C++` code provides significant increases in performance and memory conservation, but lacks the ease-of-use and flexibility of scripting languages.

`xolotl` handles this problem through symbolic manipulation of `C++` objects in `MATLAB`. Built from the ground up in `C++`, `xolotl` maintains all the advantages of custom compiled code, but can run in `MATLAB` without the user having to touch the `C++` code. `xolotl` represents compartment, conductance, synapse, and controllers as `cpplab` objects, which map to underlying `C++` header files. In this way, properties of the `xolotl` network can be examined and changed using object-oriented paradigms. The object specifies the `integrate` function, not the other way around.

5.3 APPLICATIONS OF CPPLAB

NEED TO WRITE THIS

CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

AUTHOR CONTRIBUTIONS

SG-S designed and implemented the core of the `xolotl` toolbox. AH contributed to the code base, created the online user documentation, and wrote the manuscript. EM supervised the project. All authors reviewed the paper.

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SUPPLEMENTAL DATA

Tables including all conductances packaged with `xolotl` should be put in the supplementary material.

DATA AVAILABILITY STATEMENT

The code to generate all figures is available at (`https://github.com/marderlab/xolotl-paper`). `xolotl` is frely available at (`https://github.com/marderlab/xolotl`).

REFERENCES

Baker, Monya (Sept. 13, 2016) "Why Scientists Must Share Their Research Code". In: *Nature*. ISSN: 1476-4687. DOI: 10.1038/nature.2016.20504. URL: http://www.nature.com/doifinder/10.1038/nature.2016.20504 (visited on 05/30/2018)

Brette, Romain et al. (Dec. 1, 2007) "Simulation of Networks of Spiking Neurons: A Review of Tools and Strategies". In: *Journal of Computational Neuroscience* 23.3, pp. 349–398. ISSN: 1573-6873. DOI: 10.1007/s10827-007-0038-6. URL: https://link-springer-com.resources.library.brandeis.edu/article/10.1007/s10827-007-0038-6 (visited on 05/01/2018)

Butcher, J. C. (2016) "Numerical Differential Equation Methods". In: *Numerical Methods for Ordinary Differential Equations*. Third. Wiley-Blackwell, pp. 55–142. ISBN: 978-1-119-12153-4. DOI: 10.1002/9781119121534.ch2. URL: https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119121534.ch2 (visited on 05/29/2018)

Connor, J. A. and C. F. Stevens (Feb. 1971a) "Inward and Delayed Outward Membrane Currents in Isolated Neural Somata under Voltage Clamp". In: *The Journal of Physiology* 213.1, pp. 1–19. ISSN: 0022-3751. pmid: 5575338. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1331719/ (visited on 05/26/2018)

— (1971b) "Voltage Clamp Studies of a Transient Outward Membrane Current in Gastropod Neural Somata". In: *The Journal of Physiology* 213.1, pp. 21–30. ISSN: 1469-7793. DOI: 10.1113/jphysiol.1971.sp009365. URL: https://physoc.onlinelibrary.wiley.com/doi/abs/10.1113/jphysiol.1971.sp009365 (visited on 05/26/2018)

Dayan, Peter and L. F. Abbott (2001) *Theoretical Neuroscience*. Computational neuroscience. Cambridge, Mass.: Massachusetts Institute of Technology Press. xv+460. ISBN: 978-0-262-04199-7.

Delorme, Arnaud and Simon J. Thorpe (Jan. 1, 2003) "SpikeNET: An Event-Driven Simulation Package for Modelling Large Networks of Spiking Neurons". In: *Network: Computation in Neural Systems* 14.4, pp. 613–627. ISSN: 0954-898X DOI: 10.1088/0954-898X_14_4_301. pmid: 14653495. URL: https://doi.org/10.1088/0954-898X_14_4_301 (visited on 05/01/2018)

Destexhe, Alain and Thierry Bal (Mar. 11, 2009) *Dynamic-Clamp: From Principles to Applications*. Springer Science & Business Media. 428 pp. ISBN: 978-0-387-89279-5.

Eklund, Anders, Thomas E. Nichols, and Hans Knutsson (June 28, 2016) "Cluster Failure: Why fMRI Inferences for Spatial Extent Have Inflated False-Positive Rates". In: *Proceedings of the National Academy of Sciences*, p. 201602413. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1602413113. pmid: 27357684. URL: http://www.pnas.org/content/early/2016/06/27/1602413113 (visited on 05/30/2018)

Hines, M. L. and N. T. Carnevale (Aug. 1, 1997) "The NEURON Simulation Environment". In: *Neural Computation* 9.6, pp. 1179–1209. ISSN: 0899-7667. DOI: 10.1162/neco.1997.9.6.1179. URL: https://doi.org/10.1162/neco.1997.9.6.1179 (visited on 04/30/2018)

Hodgkin, A. L. and A. F. Huxley (Apr. 1952) "The Components of Membrane Conductance in the Giant Axon of Loligo". In: *The Journal of Physiology* 116.4, pp. 473–496. ISSN: 0022-3751. pmid: 14946714.

Hodgkin, A. L., A. F. Huxley, and B. Katz (Apr. 28, 1952) "Measurement of Current-Voltage Relations in the Membrane of the Giant Axon of Loligo". In: *The Journal of Physiology* 116.4, pp. 424–448. ISSN: 0022-3751. pmid: 14946712. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1392219/ (visited on 11/16/2017)

Jolivet, Renaud et al. (Apr. 30, 2008) "A Benchmark Test for a Quantitative Assessment of Simple Neuron Models". In: *Journal of Neuroscience Methods* 169.2, pp. 417–424. ISSN: 0165-0270. DOI: 10.1016/j.jneumeth.2007.11.006. pmid: 18160135.

Kernighan, Brian and Dennis M. Ritchie (1978) *The C Programming Language*. Prentice hall.

Liu, Z. et al. (1998) "A Model Neuron with Activity-Dependent Conductances Regulated by Multiple Calcium Sensors". In: *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 18.7, pp. 2309–2320. ISSN: 0270-6474. pmid: 9502792.

O'Leary, Timothy et al. (July 9, 2013) "Correlations in Ion Channel Expression Emerge from Homeostatic Tuning Rules". In: *Proceedings of the National Academy of Sciences* 110.28, E2645–E2654. ISSN: 0027-8424, 1091-6490. DOI: 10.1073/pnas.1309966110. pmid: 23798391. URL: http://www.pnas.org/content/110/28/E2645 (visited on 02/14/2018)

Oh, Jiyeon and Donald A. French (Jan. 1, 2006) "Error Analysis of a Specialized Numerical Method for Mathematical Models from Neuroscience". In: *Applied Mathematics and Computation* 172.1, pp. 491–507. ISSN: 0096-3003. DOI: 10.1016/j.amc.2005.02.028. URL: http://www.sciencedirect.com/science/article/pii/S0096300305002183 (visited on 05/29/2018)

Sedano, T. (Apr. 2016) "Code Readability Testing, an Empirical Study". In: *2016 IEEE 29th International Conference on Software Engineering Education and Training (CSEET)* 2016 IEEE 29th International Conference on Software Engineering Education and Training (CSEET) pp. 111–117. DOI: 10.1109/CSEET.2016.36.

Sherfey, Jason S. et al. (2018) "DynaSim: A MATLAB Toolbox for Neural Modeling and Simulation". In: *Frontiers in Neuroinformatics* 12. ISSN: 1662-5196. DOI: 10.3389/fninf.2018.00010. URL: https://www.frontiersin.org/articles/10.3389/fninf.2018.00010/full (visited on 04/30/2018)

Stimberg, Marcel, Dan F. M. Goodman, et al. (2014) "Equation-Oriented Specification of Neural Models for Simulations". In: *Frontiers in Neuroinformatics* 8. ISSN: 1662-5196. DOI: 10.3389/fninf.2014.00006. URL: https://www.frontiersin.org/articles/10.3389/fninf.2014.00006/full (visited on 05/01/2018)

Stimberg, Marcel, Dan FM Goodman, et al. (July 8, 2013) "Brian 2 - the Second Coming: Spiking Neural Network Simulation in Python with Code Generation". In: *BMC Neuroscience* 14 (Suppl 1) P38. ISSN: 1471-2202. DOI: 10.1186/1471-2202-14-S1-P38. pmid: null. URL: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3704840/ (visited on 05/01/2018)

Stodden, Victoria et al. (Dec. 9, 2016) "Enhancing Reproducibility for Computational Methods". In: *Science* 354.6317, pp. 1240–1241. ISSN: 0036-8075, 1095-9203. DOI: 10.1126/science.aah6168. pmid: 27940837. URL: http://science.sciencemag.org/content/354/6317/1240 (visited on 05/30/2018)

Swensen, A. M. and E. Marder (Sept. 15, 2000) "Multiple Peptides Converge to Activate the Same Voltage-Dependent Current in a Central Pattern-Generating Circuit". In: *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 20.18, pp. 6752–6759. ISSN: 0270-6474. pmid: 10995818.

— (June 1, 2001) "Modulators with Convergent Cellular Actions Elicit Distinct Circuit Outputs". In: *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 21.11, pp. 4050–4058. ISSN: 1529-2401. pmid: 11356892.

Turrigiano, G., G. LeMasson, and E. Marder (May 1995) "Selective Regulation of Current Densities Underlies Spontaneous Changes in the Activity of Cultured Neurons". In: *The Journal of Neuroscience: The Official Journal of the Society for Neuroscience* 15 (5 Pt 1) pp. 3640–3652. ISSN: 0270-6474. pmid: 7538565.

Vitay, Julien, Helge Ülo Dinkelbach, and Fred H. Hamker (2015) "ANNarchy: A Code Generation Approach to Neural Simulations on Parallel Hardware". In: *Frontiers in Neuroinformatics* 9. ISSN: 1662-5196. DOI: 10.3389/fninf.2015.00019. URL: https://www.frontiersin.org/articles/10.3389/fninf.2015.00019/full (visited on 05/26/2018)

Xu, W., D. Xu, and L. Deng (July 2017) "Measurement of Source Code Readability Using Word Concreteness and Memory Retention of Variable Names". In: *2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC)* 2017 IEEE 41st Annual Computer Software and Applications Conference (COMPSAC) vol. 1, pp. 33–38. DOI: 10.1109/COMPSAC.2017.166.

FIGURE CAPTIONS

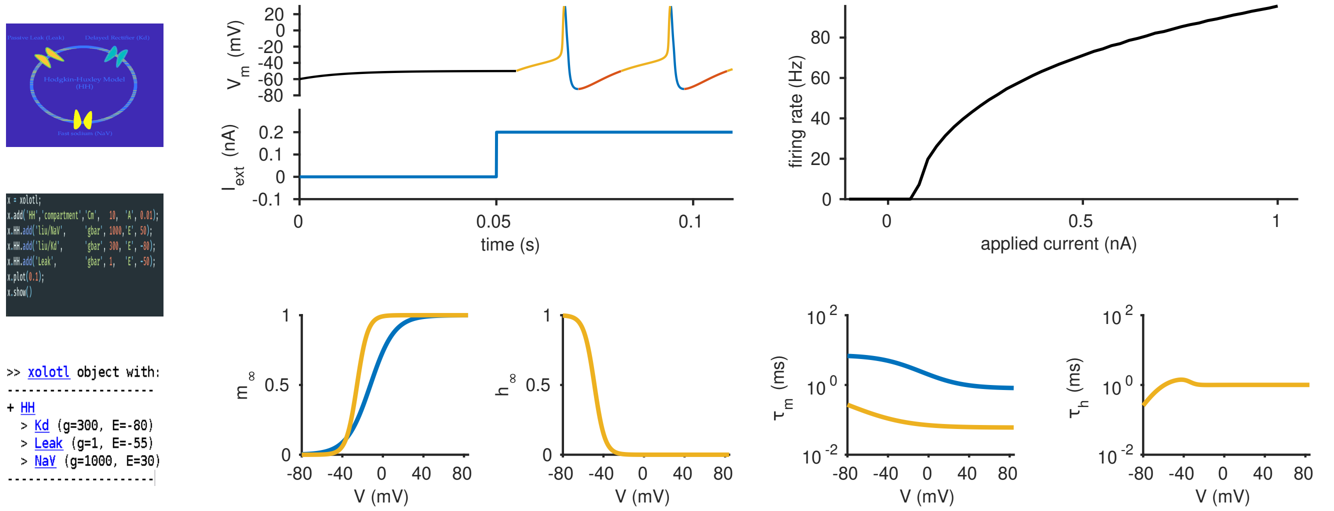

Figure 1: `xolotl` can quickly set up and simulate conductance-based models. (A) Cartoon of a Hodgkin-Huxley single-compartment neuron model with fast sodium, delayed rectifier, and leak currents. (B) Code snippet in `MATLAB` used to implement D, F-I. (C) `xolotl` schematic displayed in the `MATLAB` command prompt. (D) Simulated voltage trace of a Hodgkin-Huxley model with three conductances and 0.2 nA of injected current. Colors indicate the dominant current (gold is fast sodium, blue is delayed rectifier, red is leak). (E) Firing rate-input relation displaying firing rate as a function of injected current current. (F-G) Steady-state gating functions for activation (m) and inactivation (h) gating variables. (H-I) Voltage-dependence of time constants for activation (m) and inactivation (h) gating variables.

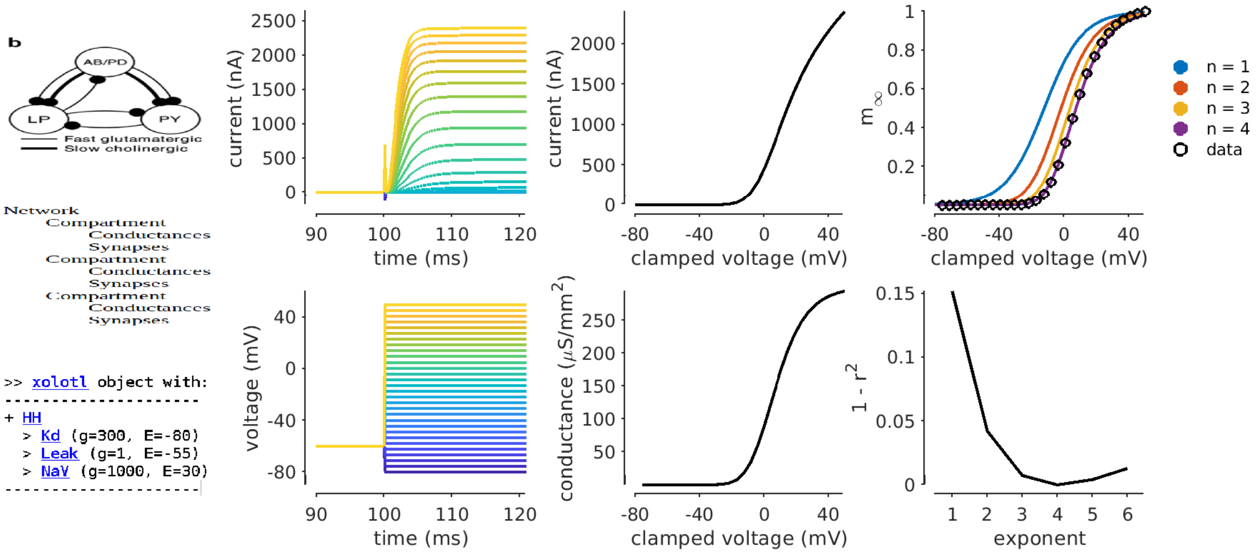

Figure 2: Simulating a voltage-clamp experiment. (A) Cartoon of a cell with delayed rectifier potassium conductance (Liu et al. 1998) with experimentally-fixed voltage. (B) Structure of `xolotl` object in A. (C) Code snippet depicting integration under voltage clamp. (D-E) Current response to steps in voltage from a holding potential of $V_m = -60$ mV. (F) Current-voltage relation of the steady-state current ($t = 400$ ms) indicating a reversal potential of $E = -80$ mV and no inactivation. (G) Conductance-voltage relation at steady-state takes the form of a sigmoid. (H) Sigmoids m fit to the model as m^n data indicating that $n = 4$ is the best fit. (I) Goodness of fit vs. exponent n, suggesting $n = 4$ as the best fit to the data.

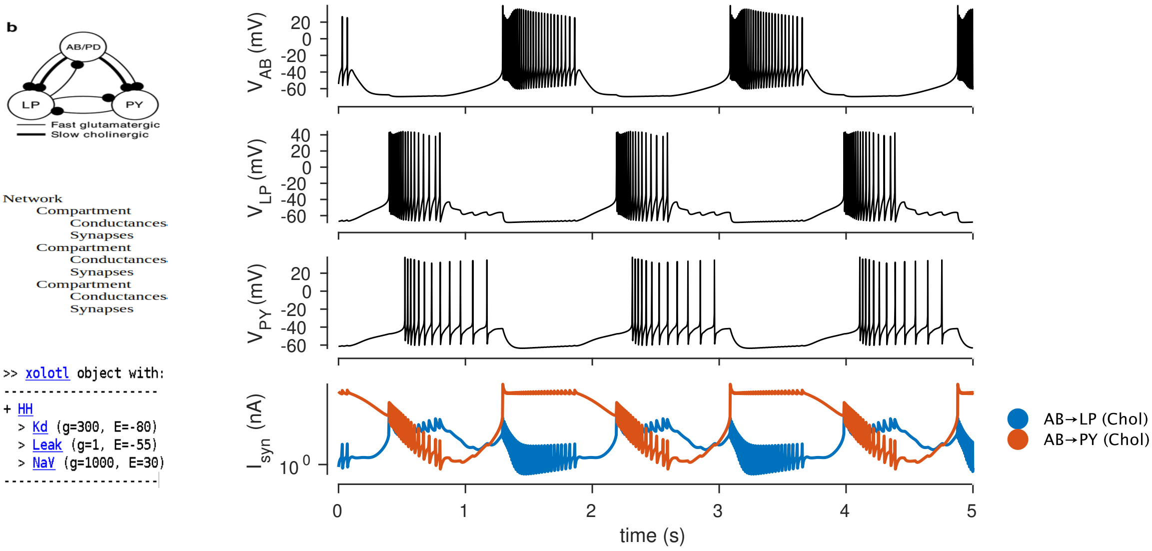

Figure 3: Simulating a network of conductance-based model neurons. (A) Diagram of a network model of the pyloric rhythm in the crustacean stomatogastric ganglion (Prinz *et al.* 2004). (B) Each neuron is modeled as a single compartment with 7-8 intrinsic conductances and 1-3 post-synaptic conductances. (C) `xolotl` implements conductances as fields of compartments and synapses as connections between compartments. (D-F) Simulated voltage trace of a model network for the three compartments. (G) Time series of synaptic currents in the simulated network can be obtained from the integration.

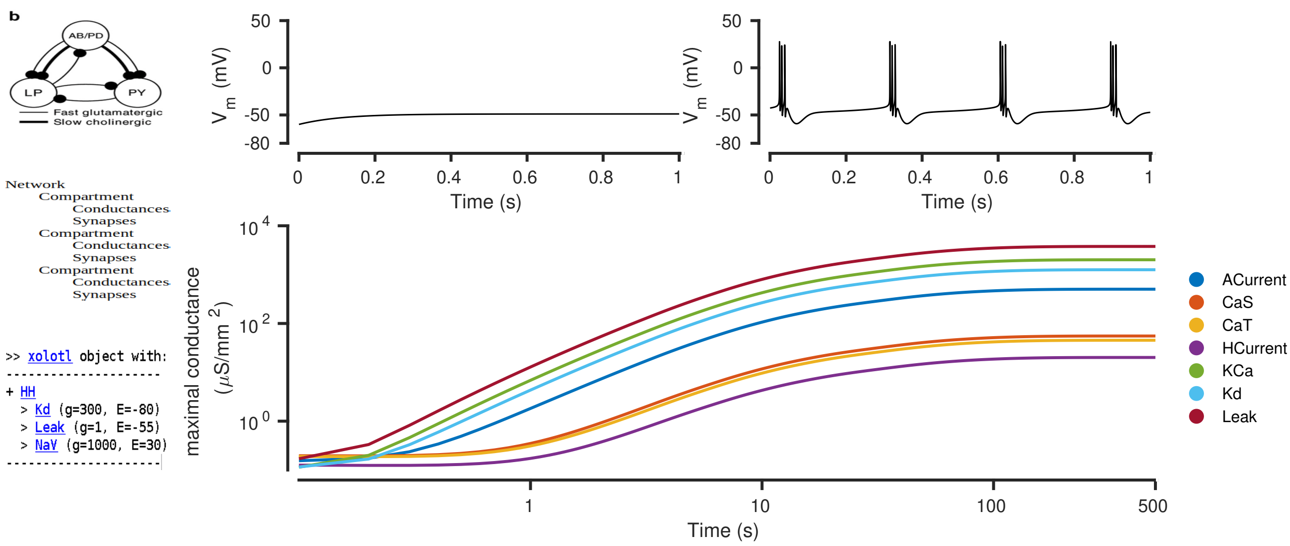

Figure 4: Simulating neurons under homeostatic regulation. (A) Cartoon of a model neuron (Liu et al. 1998) with integral control (O'Leary et al. 2013) (B) Hierarchical structure of a neuronal network considers controllers as components of compartments which act on conductances. (C) `xolotl` implements controllers as properties of conductances and synapses. (D) Calcium sensors change maximal conductances to move a neuron from quiescence to a bursting state. (E) Voltage trace shows regular bursting activity after integral control.

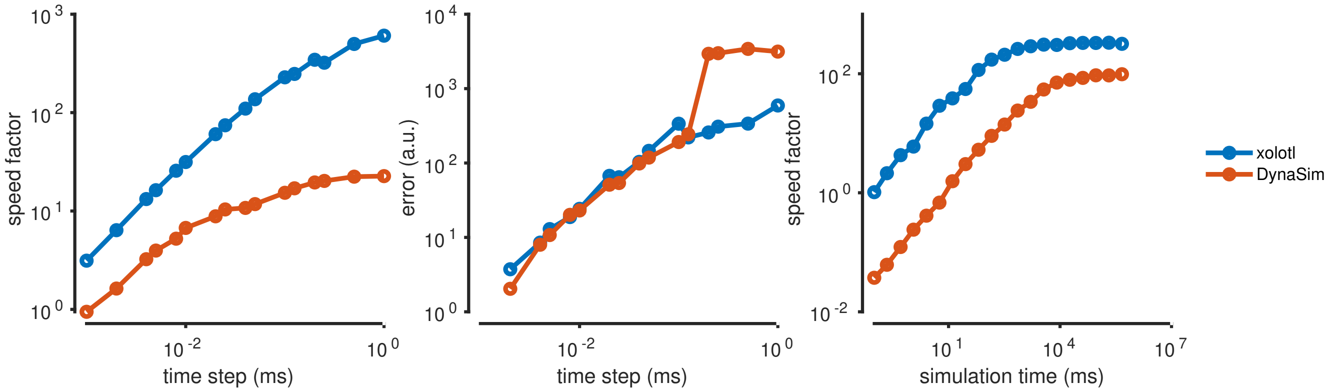

Figure 5: `xolotl` benchmarked against `DynaSim` and `NEURON`.