Biophysical Neural Spiking and Bursting Dynamics in Reconfigurable Analog VLSI

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***Abstract*—We study a range of neural dynamics under variations in biophysical parameters implementing extended Morris-Lecar and Hodgkin-Huxley models in three gating variables. The dynamics are emulated in *NeuroDyn*, an analog VLSI programmable neural emulation platform with generalized channel kinetics and biophysical membrane dynamics. We present simulation and measurement results and observe consistent agreement over a wide regime of tonic spiking and intrinsic bursting dynamics through the variation of a single conductance parameter governing calcium recovery.**

I. Introduction

Neuromorphic engineering, as an analysis by synthesis approach to computational neuroscience, is increasingly offering physical tools for studying the dynamics of complex neural systems. While analog neural chips inherently have limited programming capability, recent designs have overcome this limitation by incorporating a large number of parameters in a reconfigurable architecture [1]-[5]. This opens up opportunities in systematic studies of the dependence of the dynamics upon biophysical parameters.

Here we present such a study on a silicon biophysical neural model with wide-ranging membrane dynamics and channel kinetics [6] that, within the same architecture as illustrated in Figure 1, extends the Hodgkin-Huxley (HH) and Morris-Lecar (ML) paradigms from tonic spiking to intrinsically bursting neural dynamics [7]. The ML model has been used to study and model recordings from spinal cord neurons [8]. The analog VLSI design of the *NeuroDyn* system, and preliminary experimental results were presented in [9]. First results on coupled neural dynamics with inhibitory synapses were reported in [10]. Details on the circuit implementation and complete experimental characterization of the neural and synaptic circuits, as well as presentation of calibration and parameter fitting procedures to align neural and synaptic characteristics from models or recorded data onto the digitally programmable analog hardware are presented in [11].

We demonstrate that the addition of a slow inactivation term to the Morris-Lecar neuron model results in bursting neural dynamics in an aVLSI implementation. Systematic regression of parameters results in generation of circuit parameters to implement the model on chip. Calculation of inter-spiking interval (ISI) for both simulated and measured bursting waveforms over the variation of a single conductance parameter g_w governing calcium recovery show agreement in behavior between simulation and measurement data.

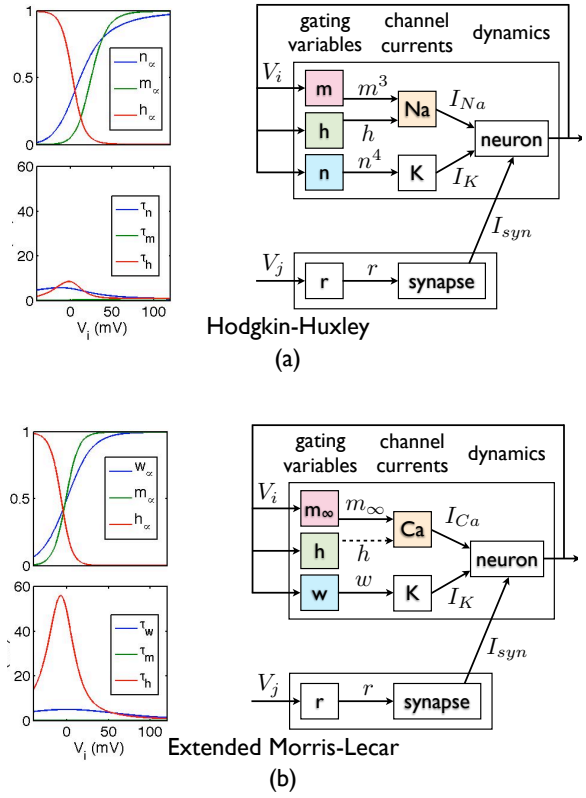

Fig. 1. The *NeuroDyn* analog VLSI programmable neural emulation platform [9]-[11] is used to generate both tonic firing and intrinsic bursting dynamics using extensions on Hodgkin-Huxley and Morris-Lecar paradigms.

II. System Overview

The *NeuroDyn* system [9]-[11] consists of 4 neurons with Hodgkin-Huxley type membrane dynamics fully connected through 12 conductance-based synapses. All parameters are individually addressable and individually programmable and

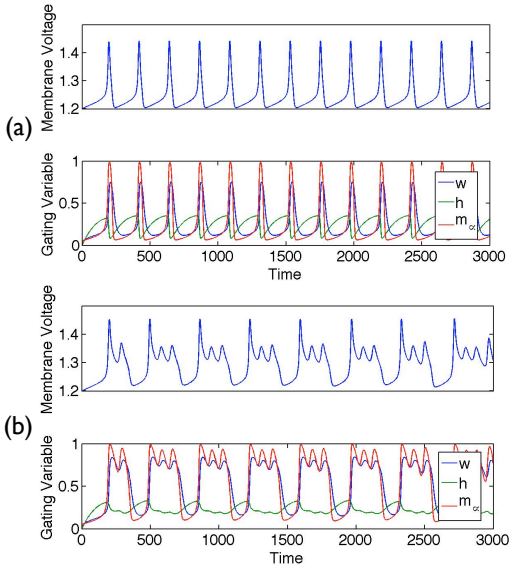

Fig. 2. Simulation data displaying membrane and gating variable dynamics in the ML model (a) and with an extension to include slow inactivation dynamics (b).

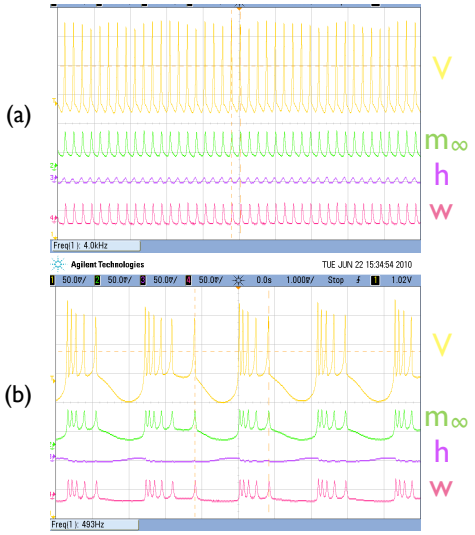

Fig. 3. Measurement data displaying membrane and gating variable dynamics in the ML model (a) and with an extension to include slow inactivation dynamics (b).

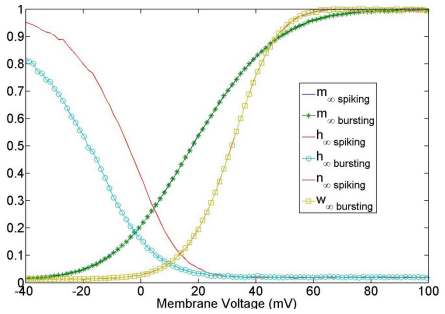

Fig. 4. Measured activation and inactivation asymptotes for gating variables m_∞, h and w in the ML with and without the intrinsic bursting extension.

are biophysically-based governing the conductances, reversal potentials, and voltage-dependence of the channel kinetics. There are a total of 384 programmable parameters governing the dynamics with each parameter stored on-chip in a 10-bit DAC.

III. Methodology

A. Membrane Dynamics

The Hodgkin-Huxley membrane dynamics [12] describe neural dynamics as a sum of conductance-based channel currents. Gating variables m, h, and n describe the voltage-dependent dynamical profiles of each channel and are described by

$$C_{mem}\frac{dV_i}{dt} = -I_{Na_i} - I_{K_i} - I_{L_i} - I_{syn_{ij}} \quad (1)$$

where $i, j = 0 \ldots 3$, and

$$\begin{aligned} I_{Na_i} &= {m_i}^3 h_i \; g_{Na_i} \; (V_i - E_{Na_i}) \\ I_{K_i} &= {n_i}^4 \; g_{K_i} \; (V_i - E_{K_i}) \\ I_{L_i} &= g_{L_i} \; (V_i - E_{L_i}). \\ I_{syn_{ij}} &= r_{ij} \; g_{syn_{ij}} \; (V_i - E_{syn_{ij}}) \end{aligned}$$

In order to emulate bursting neural dynamics, the Hodgkin-Huxley model requires the addition of a slow-modulation due to Ca inactivation dynamics. We accommodate this extra inactivation channel by first considering the two-dimensional "reduced" excitation model as described by Morris-Lecar [13]:

$$C_{mem}\frac{dV_i}{dt} = -I_{Ca_i} - I_{K_i} - I_{L_i} - I_{syn_{ij}} \quad (2)$$

where $i, j = 0 \ldots 3$, and

$$\begin{aligned} I_{Ca_i} &= m_{\infty_i} \; g_{Ca_i} \; (V_i - E_{Ca_i}) \\ I_{K_i} &= w_i \; g_{K_i} \; (V_i - E_{K_i}) \\ I_{L_i} &= g_{L_i} \; (V_i - E_{L_i}) \\ I_{syn_{ij}} &= r_{ij} \; g_{syn_{ij}} \; (V_i - E_{syn_{ij}}) \end{aligned} \quad (3)$$

We then reintroduce the variable h_i as a multiplicative term in the calcium conductance in (3), modeling the calcium recovery rather than calcium inactivation, on a slower timescale spanning several action potentials. We also revert to the cubic form of fast Ca (Na) activation in the Hodgkin-Huxley model, of the form (1). We show that we can adapt this model (1) to reproduce rich spiking and bursting dynamics, with only changes in the conductance and channel kinetics, illustrated in Fig. 1 and described below.

B. Channel Kinetics

The neuron channel gating variables are modeled by a rate-based first-order approximation to the kinetics governing the random opening and closing of membrane channels for any of

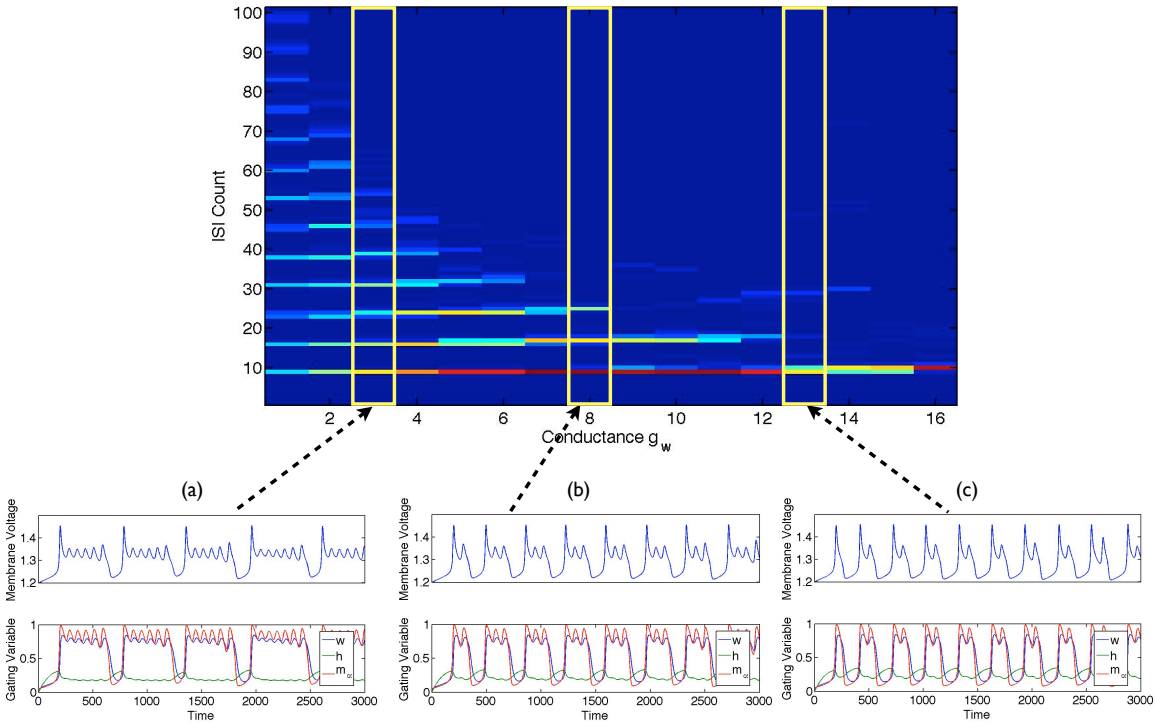

Fig. 5. Simulated intrinsically bursting neuron simulation with variation of a single conductance parameter g_w governing calcium recovery with increasing values from (a) to (c)

the gating variables x (e.g. m, h, n, w):

$$\frac{dx_i}{dt} = \alpha_{x_i}(1 - x_i) - \beta_{x_i} x_i \tag{4}$$

where each channel variable denotes the fractions of corresponding channel gates in the open state, and where the α and β parameters are the corresponding voltage-dependent opening and closing rates. The channel variables can be equivalently expressed as:

$$\tau_{x_i} \frac{dx_i}{dt} = x_{\infty_i} - x_i \tag{5}$$

with asymptotes $x_{\infty_i} = \alpha_{x_i}/(\alpha_{x_i} + \beta_{x_i})$ and time constants $\tau_{x_i} = 1/(\alpha_{x_i} + \beta_{x_i})$.

We model each of the opening and closing channel kinetics in the *NeuroDyn* system using the seven-point sigmoidal regression functions implemented as cascaded differential pairs. As described in [11], we use a least squares fit regression technique to determine the appropriate current biases to fit the generalized channel kinetic functions.

Simulation data was obtained by implementing the models described using MATLAB. The simulation and measurement data illustrating the neural spiking behavior before and after the inclusion of the slow inactivation channel are shown in Figure 2 and Figure 3. The h gating variable is set with constant channel kinetics before the inclusion of the slow inactivation channel, and results in constant regular spiking. The asymptote activation and inactivation variables in the extended ML model are shown in Figure 4.

IV. Results

We calculate the ISI histogram for each burst of spikes over the variation of a single parameter g_w governing calcium recovery [7] for both simulation and measurement data as displayed in Figure 5 and Figure 6. We observe consistent spiking behavior over a wide regime of neural dynamics. For low g_w conductance values, the neuron spikes and is followed by subthreshold oscillations. As the g_w conductance value is increased, the neuron spikes and the following subthreshold oscillations are more pronounced. And when the g_w conductance value is further increased, the neuron spikes in a bursting manner. When the g_w conductance value is further increased, the number of subsequent bursting spikes is reduced as we observed quadruplets then triplets then doublets and finally single neuron spikes. The main difference between the simulated and experimentally observed dynamics is the effect of measurement noise which manifests as random fluctuations in spike and burst rates, as well as the number of spikes per burst.

V. Conclusion

Previous studies [14] have shown intrinsically bursting neural dynamics implemented with extensions to the HH model requiring more gating variables. Other models are capable of emulating intrinsic bursting neural dynamics, such as Izhikevich's simple model [15] which uses just two dynamical variables and Mihalas-Niebur's neural model [16] which uses three dynamical variables to also govern threshold adaptation. Here we have presented a model that reproduces both tonic

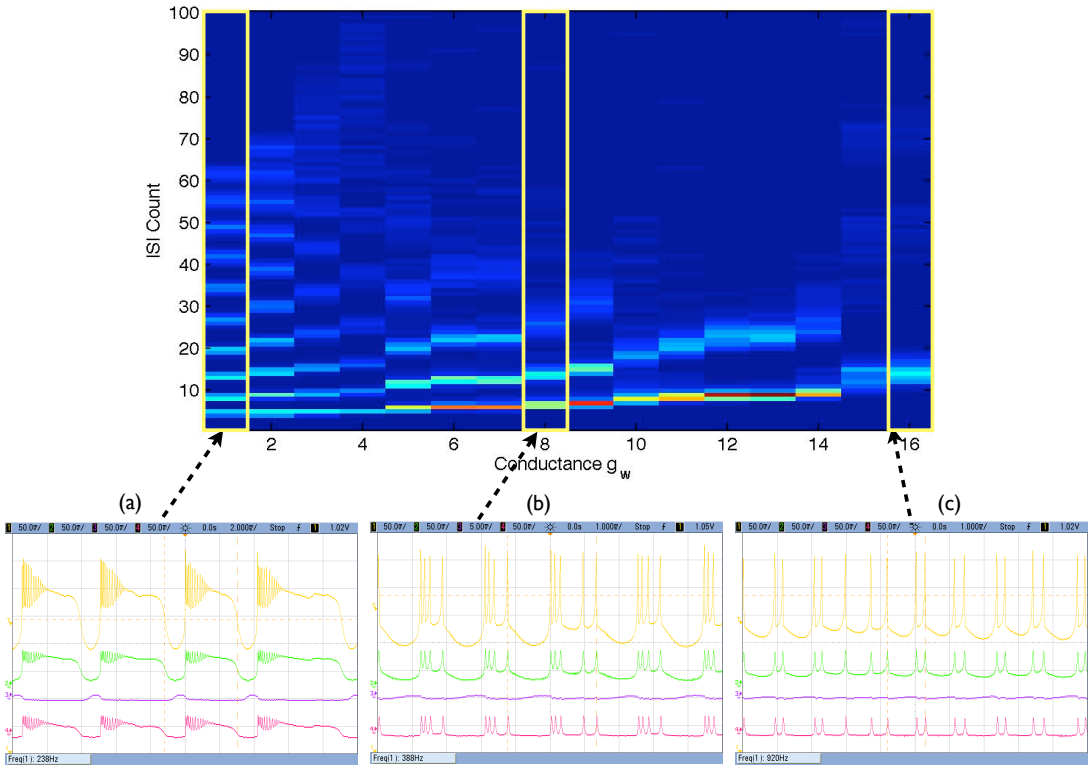

Fig. 6. Measured intrinsically bursting neuron measurement with variation of a single conductance parameter g_w governing calcium recovery with increasing values from (a) to (c)

spiking and intrinsically bursting neural dynamics in three dynamical variables that directly account for the biophysics of membranes and channels in the *NeuroDyn* neural emulation platform. We show correspondence between simulated and measured data over a wide regime of neural spiking and bursting dynamics.

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REFERENCES

[1] R.J. Vogelstein, U. Mallik, J.T. Vogelstein, and G. Cauwenberghs, "Dynamically reconfigurable silicon array of spiking neurons with conductance-based synapses," *IEEE Trans. Neural Netw.*, vol. 18, no. 1, pp. 253-265, Jan. 2007.

[2] D. Badoni, M. Giulioni, V. Dante, and P. Del Giudice, "An aVLSI recurrent network of spiking neurons with reconfigurable and plastic synapses," *Proc. IEEE Int. Symp. Circuits and Systems*, 2006, pp. 1227-1230.

[3] S. Saighi, Y. Bornat, J. Tomas, and S. Renaud, "Neuromimetic ICs and system for parameters extraction in biological neuron models," *Proc. IEEE Int. Symp. Circuits and Systems*, 2006, pp. 4207-4211.

[4] F. Tenore, R.J. Vogelstein, R. Etienne-Cummings, G. Cauwenberghs, and P. Hasler, "A floating-gate programmable array of silicon neurons for central pattern generating networks," *Proc. IEEE Int. Symp. Circuits and Systems*, 2006, pp. 3157-3160.

[5] M. F. Simoni, G. S. Cymbalyuk, M. E. Sorensen, R. L. Calabrese, and S. P. DeWeerth, "A multiconductance silicon neuron with biologically matched dynamics," *IEEE Trans. on Biomed. Eng.*, vol. 51, no. 2, Feb. 2004.

[6] A. Destexhe, Z.F. Mainen, and T.J. Sejnowski, "Synthesis of models for excitable membranes, synaptic transmission and neuromodulation using a common kinetic formalism," *J. Comp. Neurosci.*, vol. 1, pp. 195-230, 1994.

[7] E. Izhikevich, *Dynamical Systems in Neuroscience: The Geometry of Excitability and Bursting*, The MIT Press, 2006.

[8] S. A. Prescott, S. Ratte, Y. D. Koninck, and T. J. Sejnowski, "Pyramidal neurons switch from integrators in vitro to resonantors under in vivo-like conditions," *J. Neurophysiol.*, vol. 100, pp. 3030-3042, Dec. 2008.

[9] T. Yu and G. Cauwenberghs, "Analog VLSI neuromorphic network with programmable membrane channel kinetics," *Proc. IEEE Int. Symp. Circuits and Systems*, 2009, pp. 349-352.

[10] T. Yu and G. Cauwenberghs, "Biophysical synaptic dynamics in an analog VLSI network of Hodgkin-Huxley neurons," *Proc. IEEE Eng. in Med. Bio. Conf.*, 2009, vol. 1, pp. 3335-3338.

[11] T. Yu and G. Cauwenberghs, "Analog VLSI Biophysical Neurons and Synapses With Programmable Membrane Channel Kinetics," *IEEE Trans. on Biomedical Circuits and Systems*, vol. 4, no. 3, pp. 139-148, May 2010.

[12] A.L. Hogdkin and A.F. Huxley, "A quantitative description of membrane current and its application to conduction and excitation in nerve," *J. Physiol.*, vol. 117, pp. 500-544, 1952.

[13] C. Morris and H. Lecar, "Voltage oscillations in the barnacle giant muscle fiber," *J. Biophys.*, vol. 35, pp. 193-213, July 1981.

[14] T. Chay, "Modeling slowly bursting neurons via calcium store and voltage-independent calcium current," *Neural Computation*, vol. 8, pp. 951-978, 1996.

[15] E. Izhikevich, "Which model to use for cortical spiking neurons?" *IEEE Trans. on Neural Netw.*, vol. 15, no. 5, Sept. 2004.

[16] F. Folowosele, A. Harrison, A. Cassidy, A. Andreou, R. Etienne-Cummings, S. Mihalas, E. Niebur, T. Hamilton, "A Switched Capacitor Implementation of the Generalized Linear Integrate-And-Fire Neuron," *Proc. IEEE Int. Symp. Circuits and Systems*, 2009, pp. 2149-2152.