Event-based simulation strategy for conductance-based synaptic interactions and plasticity

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Available online 10 February 2006

Abstract

The immense computational and adaptive power of the cerebral cortex emerges from the collective dynamics of large populations of interacting neurons. Thus, for theoretical investigations, optimal strategies for modeling biophysically faithful neuronal dynamics are required. Here, we propose an extension of the classical leaky integrate-and-fire neuronal model, the gIF model. It incorporates various aspects of high-conductance state dynamics typically seen in cortical neurons in vivo, as well as activity-dependent modulation of synaptic weights. The analytic description of the resulting neuronal models allows their use together with the event-driven simulation strategy. The latter provides an efficient tool for exact simulations of large-scale neuronal networks.

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Keywords: Integrate-and-fire; High-conductance state; Asynchronous; STDP

1. Introduction

Although electrophysiological and neuroimaging techniques allowed huge advances in characterizing neural activity in vivo[11], these methods are subject to stringent constraints concerning their spatio-temporal resolution. Modeling approaches remain one of the main path to assess the collective dynamics of large populations of neurons on arbitrary spatio-temporal scales[5]. However, computer simulations of very large neuronal populations still go beyond the limits set by available conventional computational hardware. The reason for this limit is that biophysical models of neurons are usually described by systems of coupled differential equations which can be solved numerically only by discretization of space and time (clock-driven methods). In this case, the algorithmic complexity and computational load scale linearly with the spatio-temporal resolution. Moreover, the restriction to a fixed time-grid has an impact on the precision of the simulation[3], which might turn out to be crucial for models with spike-timing depending plasticity (STDP).

Recently, a new and more efficient approach was proposed[9], in which the computational complexity scales linearly with the number of neuronal units, independent on the temporal resolution. This event-driven simulation strategy makes use of the fact that synaptic events occur rather isolated, causing neurons to spend most of the time dynamically decoupled from the network. The most efficient implementation of this strategy is achieved if membrane equations are analytically solvable. Simulations of realistic network states must take into account the high-conductance state of cellular membranes typically seen in vivo[1], but such neuronal models are usually not analytically solvable. We present here analytic extensions of the classical leaky integrate-and-fire (LIF) model, the gIF models, which incorporate various aspects of the high-conductance state dynamics seen in cortical neurons in vivo. The analytic form of these extensions allows the application of event-driven simulation strategies, therefore providing the basis for efficient and exact simulations of large-scale networks with realistic synaptic interactions.
2. Integrate-and-fire neuron models with high-conductance state dynamics

\[
\tau \frac{m(t)}{t} + m(t) = 0. \tag{1}
\]

where \(m(t)\) denotes the membrane time constant.

Upon arrival of a synaptic input at time \(t\), the membrane time constant generalizes earlier notions which specifically focused on capturing the distance of the actual membrane state to the corresponding steady-state point.

\[
\tau \frac{\Delta m}{\tau} + \Delta m = 0. \tag{2}
\]

Here, \(\Delta m\) is the change in the effective membrane time constant after arrival of a synaptic event, the forward consequence of this transient change in membrane conductance component that adds to a constant leak conductance.

\[
m(t) = m(t_0) \left[ \frac{-t - t_0}{\tau^0} + \frac{\tau (1 - -(t-t_0)/\tau)}{\tau (t_0)} \right] - \frac{\tau (1 - -(t-t_0)/\tau)}{\tau (t_0)}. \tag{3}
\]

In real neurons, the effect of synaptic inputs can be modeled based on the temporal difference between pre- and post-synaptic event pairs [10]. Here, upon arrival of a synaptic event, the synaptic conductance component \(g_i\) to \(F\) instantaneously updates by \(g_i(t) = g_i(t_0) + C_{L, i}\) (for simplicity, the contribution of active load (Fig. 2A).

The gIF neuron model defined by Eq. (3) was extended to incorporate both the effect of the actual membrane time constant on the PSP amplitude, as well as the effect of the postsynaptic spike intervals in which synaptic weight modification of the efficacy of excitatory synaptic terminals was modeled based on the temporal difference between pre- and post-synaptic event pairs [10]. Here, upon arrival of a synaptic event, the synaptic conductance component \(g_i\) to \(F\) instantaneously updates by \(g_i(t) = g_i(t_0) + C_{L, i}\) (for simplicity, the contribution of active load (Fig. 2A).

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3. Models of STDP for use in event-driven simulations

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\]

In the case of an exponential synapse, \(G(t) = G(t)\) and \(m(t)\) denotes the membrane time constant.

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G(t) \Delta G(t) = G(t_0), \quad \tau(t) \frac{\Delta m}{\tau} + \Delta m = 0. \tag{2}
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the model of frequency-dependent dynamic synapses by Markram et al. [8], or the STDP model of Froemke and Dan [2] incorporating spike triplet interactions. In all cases, we observed no significant increase in the computational load for comparable network size and connectivity. In the computationally most expensive model, about 10^6 events can be modeled in real-time without specific optimization of the simulation code using NEURON [4] on a 3 GHz Pentium 4 processor running under the Linux operating system. Scripts for the gIF neuron models are available at http://cns.iaf.cnrs-gif.fr/.

4. Discussion

Here we presented an extension of the classical LIF neuron model by incorporating conductance-based synaptic interactions and synaptic plasticity. This gIF model is explicitly solvable or allows analytic approximations, which open the possibility for using it in event-driven simulation strategies. This provides a novel framework for simulating large-scale neural networks with realistic synaptic interactions, and therefore realistic emergent network states, such as high-conductance states.
Acknowledgements

Research supported by CNRS, HFSP and the EU (IST-2001-34712, IST-2005-015879).

References


Fig. 2. Simulations with biophysically detailed and simple integrate-and-fire neurons. (A) Performance evaluation of the biophysical model (BM), the LIF and gIF neuron models. The time for simulating 100 s neural activity is shown as a function of the total synaptic input rate for clock-driven (time resolution: 0.1 ms for BM, 0.01 ms for LIF) and event-driven simulations. Whereas in the investigated input parameter regime the gIF neuron models were only about 3 times slower than the LIF neuron models, the BM showed an about 600 times performance deficit. (B) Time evolution of the synaptic weight distribution in a single postsynaptic cell together with example weight histograms for a model of STDP [10]. In accordance with [10], weights stabilize already after a few thousand seconds in a bimodal distribution.