ARTICLE IN PRESS

Journal of Physiology - Paris xxx (2017) xxx–xxx

Contents lists available at ScienceDirect

Journal of Physiology - Paris

journal homepage: www.elsevier.com/locate/jphysparis

Original Research Paper

Digital hardware implementation of a stochastic two-dimensional neuron model

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ARTICLE INFO

Article history:
Received 29 July 2016
Received in revised form 9 February 2017
Accepted 17 February 2017
Available online xxxx

Keywords:
Neuromorphic engineering
Stochastic neuron
Spiking neuron model
Noise
FPGA silicon neuron

ABSTRACT

This study explores the feasibility of stochastic neuron simulation in digital systems (FPGA), which realizes an implementation of a two-dimensional neuron model. The stochasticity is added by a source of current noise in the silicon neuron using an Ornstein–Uhlenbeck process. This approach uses digital computation to emulate individual neuron behavior using fixed point arithmetic operation. The neuron model's computations are performed in arithmetic pipelines. It was designed in VHDL language and simulated prior to mapping in the FPGA. The experimental results confirmed the validity of the developed stochastic FPGA implementation, which makes the implementation of the silicon neuron more biologically plausible for future hybrid experiments.

1. Introduction

Biological neurons are characterized by a high degree of irregularity. The spike train of individual neurons is far from being periodic. Neurons have been found noisy both in the generation of spikes and in the transmission of synaptic signals. Many 'in vivo' experiments of neuronal activity show noisy behaviors and subthreshold membrane potential oscillations. The noise comes from intrinsic source that generates stochastic behavior on the level of the neuronal dynamics, and extrinsic sources that arise from network effects and in the transmission of synaptic signals (Manwani and Koch, 1999). In addition a source of noise, which is omnipresent, is the thermal noise. As the noise affects neural computation, there is a long tradition of theoretical studies aimed at understanding the impact of noise on the integrative properties of neurons (Stein et al., 2005). A large number of theoretical studies have designed simplified models to study the effect of noise in neurons. Usually the synaptic activity is modeled by a source of current noise in the neuron (Levitan et al., 1968; Tuckwell, 1988) or by fluctuating conductance (Destexhe et al., 2001), and thus the neuron membrane potential is described by a stochastic process. As results, the neuronal dynamics are modeled by stochastic differential equations. Many studies have provided evidence that this stochasticity is crucial for the overall dynamic behavior of neurons (Chow and White, 1996; Schneidman et al., 1998; White et al., 2000). The noise plays a beneficial role at least by inducing neuronal variability (Ermentrout et al., 2008), tuning the degree of synchrony between neurons (Casado, 2003; Béhuret et al., 2015) and enhancing the sensitivity of neurons to environmental stimuli (Wiesenfeld and Moss, 1995). The effect on synchrony could further relate to neural disorders such as Parkinson's disease (Hammond et al., 2007). Moreover, studies on spinal nerve injury have provided evidence that in the presence of noise, the recorded membrane potential given by the dorsal root ganglia (DRG) neuron, exhibits high frequency subthreshold oscillations combined with a repetitive spiking or bursting that play a role in the Neurophatic Pain (Amir et al., 1999; Liu et al., 2000).

The exploration of noise and its effect on neurons and networks is a fascinating subject, which can have far-reaching consequences.

Understanding the effect of the noise is thus crucial both for computational neuroscience and for improving the treatments to these neural diseases. Nowadays, two approaches coexist in the neuromorphic design community: neuro-inspired methods, and neuromimetic methods. Neuro-inspired designers develop new solutions to solve engineering issues. They use biological principles, taking various approximations of nature, with the view to building more efficient systems. The second approach in the neuromorphic community concerns neuromimetic systems, which imitate more precisely the activity of biological cells and could replace the living part. A neuromorphic system facilitates the

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http://dx.doi.org/10.1016/j.jphysparis.2017.02.002
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building of a hybrid network incorporating both silicon and biological neurons. This technique consists of connecting artificial and biological neurons to create a real-time closed-loop (Sorensen et al., 2004). Many research groups have been designing and exploiting neuromimetic silicon neurons that could be digital, analog, or mixed, in collaboration with neuroscientists (Levi et al., 2008; Yu and Cauwenberghs, 2010; Indiveri et al., 2011; Grassia et al., 2011; Brink et al., 2013; Kohno and Aihara, 2014; Kohno et al., 2016; Nanami and Kohno, 2016). Recently, FPGAs have been used to build spiking neuronal networks (Ambroise et al., 2013; Bonabi et al., 2014). Digital FPGA implementations offer a significant speedup over software designs, as well as size, weight, and power efficiency. Compared to analog VLSI, digital FPGAs designs are stable, scalable, and flexible in design alterations. Previous works have already implemented Neuron on FPGA (Cassidy and Andreou, 2008; Cassidy et al., 2013). However, those designs have been realized for computation purposes without taking into account stochasticity. In the work of Bonabi et al., 2014 where digital implementation of the Hodgkin-Huxley neuron model (1952) has been done, a random term that creates small differences between neurons, was added as noise term to the input current of each neuron in order to add the effect of stochastic factors. The noises are generated from a zero mean Gaussian distribution for each Hodgkin-Huxley neuron. Because it uses a ROM table for random number generation, it requires a large amount of memory resources.

In this work we explore the feasibility of stochastic neuron simulation in digital systems (FPGA), which realizes an implementation of the quartic neuron model (Touboul, 2008) that is a two-dimensional neuron model with a richer bifurcation diagram than Izhikevich model (Izhikevich, 2003). Furthermore, the noises are generated with an online generation approach that reduces the resource consumption into the FPGA.

2. Methods

2.1. Choice and presentation of the neuron model

A biological neuron model (also known as a spiking neuron model) is a mathematical description of the properties of nerve cells, or neurons, which is designed to accurately describe and predict biological processes. Models that describe the membrane potential of a neuron by a single variable and ignore its spatial variation are called single-compartment models. In this sub-class of models, the rich and complex dynamics of real neurons can be reproduced quite accurately by models that include aspects of ionic conductances as proposed by Hodgkin and Huxley (1952) with a four-dimensional set of equations that describes the ionic conductance's dynamics of the giant axon. Several simple two-dimensional models have been recently introduced (Izhikevich, 2003; Kohno and Aihara, 2014; Kohno et al., 2016; Nanami and Kohno, 2016).

They propose a trade-off between simplicity of equations and variation of dynamical behavior, each of them is optimized to specific activities to be effectively simulated. The choice of model was based on two criteria: the family of neurons able to be reproduced and the number of equations. Among these models, the quartic neuron model (Touboul, 2008) can reproduce biological behaviors observed experimentally and also can exhibit sustained sub-threshold oscillations. In a previous work (Grassia et al., 2014), we proposed a digital hardware implementation of the quartic neuron model, taking into account biological real time, which can emulate the electrophysiological activities in various types of cortical neurons with diversity similar to that of neuronal cells.

In the present work we propose a stochastic digital hardware implementation of the quartic neuron model in which the stochasticity is added by a source of current noise in the neuron model using an Ornstein–Uhlenbeck process, which makes the digital hardware implementation more biologically plausible. The implementation into the FPGA is done using fixed point arithmetic operation and taking into account biological time scale.

2.2. Equations and numerical integration of the neuron model

The dynamics of the quartic spiking neuron model are defined by two coupled differential equations, and a reset condition. This model is described by two variables, the membrane potential v and a variable w representing membrane recovery, whose dynamics are governed by the following differential equations:

$$\begin{cases} \dot{v} = v^4 + 2av - w + I \\ \dot{w} = a(bv - w) \end{cases} \tag{1}$$

where I is the synaptic input and a, b are parameters controlling the dynamical behavior of the neuron model. The neuron emits a spike when its membrane potential crosses a constant threshold. Let α be our threshold. When a spike occurs, the membrane potential is instantaneously reset to some value v_r and the variable w is increased:

$$\text{If} \quad v(t^-) > \alpha \quad \text{then} \quad \begin{cases} v(t) = v_r \\ w(t) = w(t^-) + d \end{cases} \tag{2}$$

where v_r, d are parameters controlling the neuron reset behavior.

In the present work, the stochasticity is added by a source of current noise in the neuron model. The synaptic current I is modeled by a stochastic process, as explained below, using an Ornstein–Uhlenbeck process X_t. The neuron membrane potential is then described by a stochastic process.

The Ornstein–Uhlenbeck process is a prototype of a noisy relaxation process and is an example of a Gaussian process that has a bounded variance and admits a stationary probability distribution. The process is stationary, Gaussian and Markovian. It satisfies the following stochastic differential equation:

$$dX_t = \theta(\mu - X_t)dt + \sigma dW_t \tag{3}$$

where μ, $\theta > 0$, $\sigma > 0$ are parameters and W_t denotes the Wiener process.

The parameter μ represents the equilibrium or mean value for the process. The stationary variance is given by:

$$\mathrm{var}(X_t) = \frac{\sigma^2}{2\theta}.$$

This form of current may represent an approximation to that resulting from the random opening and closing of ion channels on a neuron's surface or to randomly occurring synaptic input currents with exponential decay (Tuckwell et al., 2002). As results, the neuronal dynamics are modeled by stochastic differential equations (SDEs). We consider the resulting integrals as Itô-integrals and use the Euler–Maruyama method (Higham, 2001) for simulating different realizations of the system. The simulations are carried out using the MATLAB programming environment. Each equation defined in the continuous time domain must be mapped to discrete time for numerical implementation. The Euler–Maruyama method is a procedure for the approximate numerical solution of SDEs. It is a simple generalization of the Euler method for ordinary differential equations to SDEs. The simulation using the forward Euler–Maruyama only depends on past values of state variables and state derivatives which is thus an explicit integration algorithm useful for FPGA implementation.