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Letters

Dynamics of VLSI analog decoupled neurons

Luciana Carota *

Via Guido Rosato 6, CAP. 66034 Lanciano, Chieti, Italy

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ABSTRACT

Electronic devices modeling the behavior of neural systems interacting with a natural environment are mainly composed of sensory devices and coupled spiking neural networks. In this context, the possibility to apply theoretical predictions on populations of analog VLSI neurons is aimed in view of their quantitative control. The purpose of this work is to state robust and scalable methods to obtain a quantitative match between experiments and theory for the spiking activity of non-interacting analog VLSI neurons. The decoupled neural dynamics is the starting point for the quantitative description of network coupled conditions. An empirical measure of the capacity, by which the VLSI neurons integrate the currents, an automatic calibration of the injected currents and few basic formulas allow the complete control of the neural dynamics.

1. Introduction

Electronic devices trying to model the behavior of a neural system are often termed "neuromorphic", after Carver Mead pioneered their development in the early 1990s [1]. In order to propose precise methods for achieving predictions on the stochastic dynamic behavior of a class of neuromorphic chips, the activity of a decoupled analog VLSI neural network of a small size was analyzed.

Though continuously evolving, the landscape of neural processing models (for both biological and artificial neural populations) has various landmarks based on the *Mean Field* approach (see for example [3–8]). The theory employed for the chip control is based on the *Mean Field* approach and the depolarization *diffusion approximation* presented in [8,3].

In neuromorphic modular systems, Integrate and Fire neurons directly receive stochastic input currents from sensory devices or from other recurrent spiking chips. In such systems, like in biology, the afferent currents, resulting from input Poisson pulses, are widely considered to be well approximated by a Gaussian distribution [2]. The main difference with respect to the previous papers [9–11] consists in the employment of an external Gaussian stimulation. Whereas [10] exploits Gaussian currents only to investigate the frequency response of a VLSI neuron, this work also studies the depolarization probability density.

Moreover it is shown that an empirical measure of the capacity, by which the neurons integrate the currents, captures the effects of the irregularity of the circuits and an automatic calibration procedure of the external Gaussian and constant currents is necessary to limit the irregularity among the spiking rates of the VLSI decoupled neural population.

2. VLSI network and experimental environment

This section presents the main features of the neural chip (for details see [10]) and of the experimental environment. The VLSI recurrent network is implemented in a $3.16 \times 3.16\ \mathrm{mm}^2$ standard $0.6\ \mu\mathrm{m}$, 3 metals, CMOS chip. It contains 21 integrate-and-fire neurons.

External stimulation is sent to the chip by using a series of current values: these values are sequentially written on DACs, which are mapped with the neurons and act as current injectors. The spike event times are recorded by an electronic board communicating with the PCI Bus of a PC [12,13]. Digital simulations of the VLSI network were implemented in MATLAB (SIMULINK package) to represent only the theoretical model of a decoupled neuron population. These simulations are conceived to demonstrate that, despite the electronic irregularities, it is possible to reach such a reliable quantitative control on the VLSI network so that a MATLAB implementation of its theoretical model can exactly reproduce its dynamics.

Software interface procedures implement an automatic calibration of the neuron response by the tuning in real time of current mean and variance, achieving a mean and a variance of

* Tel.: +39 087244826; fax: +39 051247244.
E-mail address: luciana.carota@gmail.com

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the Inter Spike time Interval (*ISI*) within a limited ranges of values. These procedures make uniform the network spiking rates. The calibration is based on a real time feedback mechanism: it recursively sets the current values according to the mean and the variance of the spiking rates ($1/ISI$) which have been measured in the previous step.

3. Decoupled network dynamics

Starting from the current integration model in a VLSI neuron [3], this section presents methods to control the neural dynamics inside the chip. The match between the theory, the VLSI implementation and the simulation for the neuron dynamics support the following results: the statistical parameter of the injected Gaussian currents can be finely tuned and measured; under the Gaussian stimulation, the theory for the depolarization distribution well describes both the chip neuron and the simulated one.

3.1. Neuron dynamics model

The network is composed of integrate-and-fire electronic neurons with constant leak, functionally equivalent to those described in [1] and theoretically studied in [3]. These neurons integrate linearly the total afferent current and, when the depolarization V crosses a threshold θ, a spike is emitted and the membrane potential is reset to H. The sub-threshold dynamics can be described by the equation governing the voltage across a capacitor

$$V(t)-V(t_0) = -\frac{I_\beta}{C}(t-t_0)+\frac{1}{C}\int_{t_0}^{t} I(t')\,dt', \tag{1}$$

where $I(t)$ is the sum of the external current and the pre-synaptic currents, I_β is the leak current and C is the soma capacitance. The total input current could be negative, therefore the above equation must be accompanied by the condition that V cannot go below a minimal value V_{rest}, which is a reflecting barrier. Note that $V_{rest}<H$. Making the assumption that the afferent current is a sum of independent Poisson processes resulting in a Gaussian distribution [2], and that far from the threshold θ and the reflecting barrier V_{rest}, the neuron depolarization is a stochastic diffusion process, then the $V(t)$ dynamics is well described by

$$dV(t) = \mu(t)\,dt+\sigma(t)z(t)\sqrt{dt} \tag{2}$$

where μ and σ are the mean and the standard deviation of the current for a unit of capacity and $z(t)$ is a Gaussian variable with a zero mean and unit variance (for details see [3,14]). With the Gaussian stimulation protocol, noting that $dV(t)/dt=(I(t)-I_\beta)/C$ (Eq. (1)) and starting from Eq. (2), we can calculate the mean and variance of $dV(t)/dt$ versus the statistical parameters of the current values sequentially written on DACs

$$\mu_{th} = \frac{(I_{ext}-I_\beta)}{C} \tag{3}$$

$$\sigma_{th}^2 = \frac{\tau\sigma_{ext}^2}{C^2} \tag{4}$$

where I_{ext} is the mean of the current values written on DACs and σ_{ext}^2 the variance, τ the time step between two successive DAC writings of I_{ext} and I_β is set to a constant value on the chip.

3.2. μ and σ setting by an automatic tuning

For a constant input current I_{ext} ($\sigma_{ext}=0$), the time behavior of the neural depolarization $V(t)$ is periodical: $V(t)$ linearly increases from the reset potential H to the emission threshold θ in a fixed time interval (Δt), which depends on the value of I_{ext} and on the integration capacity (C). Δt can be extracted from the recorded spike emission times and ΔV equals $\theta-H$. Then, through the values of Δt and ΔV, which are known for all the neurons, $\mu=dV(t)/dt$ is easily measured versus the constant input current (I_{ext}) (with $I_\beta=0$ mA) and the distribution of input neural capacities can be extracted from the equation $dV(t)/dt=I_{ext}/C$. The capacity C, through which the neurons integrate the currents, is the sum of all involved capacities (including the parasitic ones) inside the neuron circuit. The capacity distribution is very inhomogeneous: for example neuron 1 shows $C=461$ pF, neuron 4 shows $C=123$ pF and neuron 8 shows $C=194$ pF. Because of the differences among the capacities, the neural emission rates are also very different for the same value of the external input current. For Gaussian stimulation some examples are reported: setting $(I_{ext}-I_\beta)=0$ μA and $\sigma_{ext}=0.017$ μA, the neurons 1, 4 and 8 emit spikes at the rates 5 Hz, 11 Hz and 8 Hz respectively; with $(I_{ext}-I_\beta)=0.01$ μA and $\sigma_{ext}=0.042$ μA, the spiking frequencies are 52 Hz, 193 Hz and 95 Hz; for $I_{ext}-I_\beta=0.02$ μA and $\sigma_{ext}=0.025$ μA, the rates are 74 Hz, 244 Hz and 160 Hz.

As the current calibration is necessary (considering the variances among emission frequencies) and the capacities must be measured for calculating the current statistical parameter μ_{th} and σ_{th} (Eqs. (3) and (4)) for all the neurons, automatic procedures have to be implemented for large VLSI neural networks.

After an automatic calibration of the Gaussian current, the theoretical predictions of μ_{th} and σ_{th} (Eqs. (3) and (4)) are checked: if the depolarization V is sampled with a temporal step $\tau_{exp}>\tau$, where $\tau=1$ ms is the time between two DAC writings of I_{ext}, the experimental mean and the variance are calculated as

$$\mu_{exp} = \frac{\langle dV\rangle}{\tau_{exp}} \tag{5}$$

$$\sigma_{exp}^2 = \frac{\langle dV^2\rangle-\langle dV\rangle^2}{\tau_{exp}} \tag{6}$$

where dV is the difference between the two successive samples of V.

There is a very good concordance for the positive mean (for example ($\mu_{th}=46.7$ V/s, $\sigma_{th}^2=7.3$ V^2/s) and ($\mu_{exp}=46.3$ V/s, $\sigma_{exp}^2=7.4$ V^2/s)), whereas we can see the effects of the reflecting barrier V_{rest} for the negative mean (for example ($\mu_{th}=-28.6$ V/s, $\sigma_{th}^2=18.1$ V^2/s) and ($\mu_{exp}=-11.4$ V/s, $\sigma_{exp}^2=10.8$ V^2/s)). The large variance and very negative mean imply that the depolarization spends a lot of time near the reflecting barrier V_{rest}, that prevents μ_{exp} and σ_{exp}^2 reaching the values expected by the Eq. (3), which does not consider the presence of the reflecting barrier. Improvements of the (μ_{th}, σ_{th})-computation will be considered in future works.

3.3. Depolarization probability density

Once it has been demonstrated that it is possible to control the VLSI neuron integration of the Gaussian current, the theoretical probability density of the depolarization V is validated by a comparison between the chip and the simulated neuron behavior.

In Fig. 1, the probability density of V is experimentally represented by histograms of depolarization samples, and theoretically by a black line (for details on how to calculate the theoretical equation see [3]): in the left column the depolarization for the VLSI neuron, in the right column is the simulated neuron result. In the simulations, for the positive mean of input current (first 3 rows) the values of μ_{th} and σ_{th} are employed to stimulate the neuron, whereas for the negative mean (last 3 rows) μ_{exp} and σ_{exp} are used. The match is good for all of the cases of positive mean current if the translation of the histograms from the