ESANN'2004 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 28-30 April 2004, d-side publi., ISBN 2-930307-04-8, pp. 417-422

Implementation and coupling of dynamic neurons through optoelectronics

Alexandre R.S. Romariz

Departamento de Engenharia Elétrica, Universidade de Brasília
Caixa Postal 04386, Brasília, DF, Brasil, 70351-707.
romariz@ene.unb.br

Kelvin H. Wagner

Optoelectronic Computing Systems Center
University of Colorado, Boulder, CO, USA, 80309-0425

Abstract. In this work we describe experimental results regarding an optoelectronic implementation of a dynamic neuron model. The model is a variation of the FitzHugh-Nagumo equations, and it is implemented with linear optics and simple linear electronic feedback. The demonstration of dynamic features of the isolated neuron and of optical coupling between neurons is discussed, as well as the computational perspective of large arrays of such neurons.

1 Introduction

Optics technology has long been studied as a potential implementation of neural hardware, offering the advantages of parallelism and massive interconnection. Previous works in optical implementation of artificial neural networks have covered nearly all the common architectures, including multilayer feed-forward networks, associative memories [1], competitive learning, and self-organizing maps [2].

In defining computation-oriented neural models, it is common to abstract away the details of the actual neural dynamic behavior and its pulse-producing mechanisms. This approach corresponds to the so-called rate-code hypothesis, according to which the pulse rate is the variable being encoded in neural activity. The idea that the specific timing of the pulses may bear information (the time-code hypothesis) has only recently gained attention in neural computation studies.

Time-based representation may be designed to exhibit interesting invariances. Decisions based on a few spikes only (instead of a time-based average of many spikes

This work was partially supported by a Doctorate Scholarship to the first author from the Brazilian Research and Technology Development Council (CNPq)

ESANN'2004 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 28-30 April 2004, d-side publi., ISBN 2-930307-04-8, pp. 417-422

in order to estimate the rate) can lead to faster recognition times [10]. Finally, time-based representations can use a combination of continuous and discrete computational primitives, combining the strengths of both approaches [9].

Previous optical implementations of neural hardware have not, for the most part, explored neural dynamic models. Hardware implementation of truly dynamic neural models are just starting to emerge. We describe here an optoelectronic approach to implementing a dynamical system similar to the FitzHugh-Nagumo (FN) neural model. Experimental results are discussed, and the computational perspective of this approach is presented.

2 Model and basic implementation idea

The FitzHugh-Nagumo (FN) neural model [8], is a mathematical abstraction of neural dynamics, reducing the number of variables in the Hodgkin-Huxley Equations to only two. The first one (v) is the excitable variable (related to the membrane voltage in more complex models), while the second one (w) is a slower recovery variable, summarizing the various dynamics that causes the neuron to return to its resting state. Those two equations evolve according to

$$\begin{aligned} \tau_v \dot{v}(t) &= f[v(t)] - w(t) + u(t) \\ \tau_w \dot{w}(t) &= Av(t) - B - w(t), \end{aligned} \tag{1}$$

where u(t) is an external input. In the original work, $f[v]$ was a third-degree polynomial having three real roots in the region of interest, $f[v] = v(1-v)(v-a)$, with $0 < a < 1$. This model was implemented electronically with tunnel diodes, and more recently with piecewise linear functions [5].

The use of optics to produce nonlinear behavior is challenging, as the nonlinear response of most media to light is very weak. Hybrid approaches, in which a detected optical signal is fed back to modulate the optic source are advantageous in that perspective. Modulating the laser wavelength is an alternative way to obtaining nonlinear dynamics [3]. The fundamental idea behind this approach is that the intensity output of a linear optical system can vary nonlinearly with wavelength by means of spectrally selective filters. If this output is detected and used to drive the electronic system that modulates the laser wavelength, complex dynamics can result.

Consider a birefringent material placed between crossed polarizers (Figure 1). Even though the propagation of the field through the material is a linear phenomenon (a linear phase difference among orthogonal polarization components is generated), the output power as a function of incident wavelength is sinusoidal. In semiconductor lasers, and Vertical Cavity Surface Emitting Lasers (VCSELs) in particular, an input current i produces a small modulation in the radiation wavelength $\lambda(i)$. A simple nonlinear feedback loop can then be established, by feeding the detected signal back to the driver. This basic arrangement has been used to investigate chaotic behavior in delayed-feedback tunable lasers [3] . It is used here as the nonlinearity for an optical self-pulsing mechanism in order to implement neural-like pulses based on the dynamical system shown in Equation 1. The simple RLC circuit implements the linear part of the dynamics, the current

ESANN'2004 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 28-30 April 2004, d-side publi., ISBN 2-930307-04-8, pp. 417-422

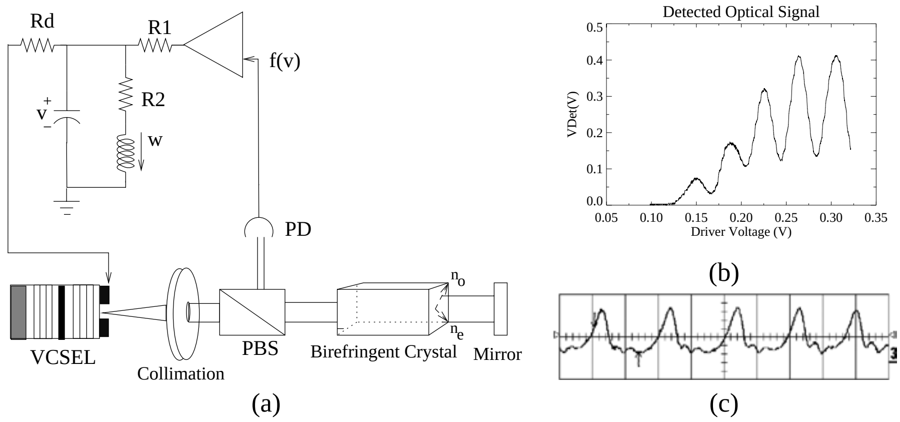

Figure 1: (a) Experimental setup for the wavelength-based nonlinear oscillator. (b) Non-monotonic mapping f(v) from driving voltage to detected signal. (c) Experimental evidence of self-pulsing regime at 1.2MHz, obtained when the VCSEL is biased.

through the inductor branch representing the w variable in Equation 1. The nonlinear function $f[v]$ is represented by the mapping from VCSEL driver voltage do detected signal.

3 Dynamical features and coupling

The intuitive idea of using a sinusoidal mapping instead of FitzHugh's third-degree polynomial can be made more rigorous with the help of stability analysis. Neural responses can be broadly separated into two classes: a class of **integrators**, or neurons that decay exponentially to rest in the absence of excitation and whose response to input pulse frequency is monotonic in a large range of values, and **resonators**, neurons which have natural oscillations in their unforced dynamics, and in consequence respond preferably to a small range of input frequencies [4]. These two different behaviors can be traced to two different process of stability loss.

We call the implemented neuron model a modified FN model in the sense that the resulting bifurcation process belongs to the same class as the original model. In particular, the FN model is a resonator. It has an Andronov-Hopf bifurcation, characterized by complex eigenvalues at the bifurcation point [4].

The isolated system exhibit the basic properties of integration, threshold, refractoriness and recovery. In Figure 2a, we show that the same system, with slightly different electronic feedback (band-pass instead of low-pass), can exhibit bursting behavior. The wavelength modulation mechanism explored in these experiments depends on heat dissipation through the VCSEL cavity, a relatively slow mechanism that limits operation to the MHz range. Other modulation effects do exist, however, that can be explored well into the GHz range.

An important feature of this implementation is that it naturally combines optical and

ESANN'2004 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 28-30 April 2004, d-side publi., ISBN 2-930307-04-8, pp. 417-422

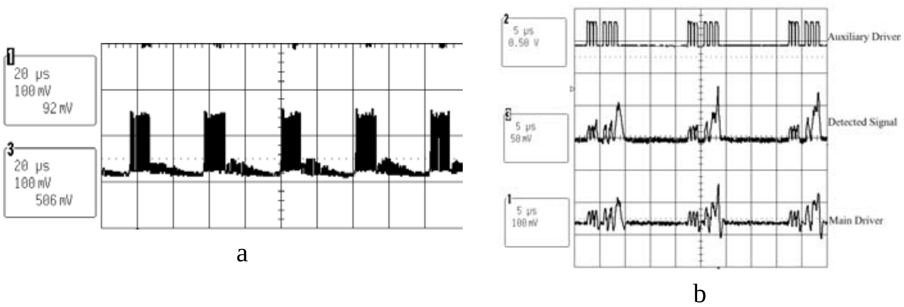

Figure 2: (a) Experimental evidence of bursting with a bandpass electronic feedback. (b) Verification of the resonant behavior of the neuron and of the effect of optical inputs. First line: driver waveform for an optical source incident on the photo-detector. Second line: Detected signal from the neuron optical output.

electrical inputs, because it has an optical detector as part of the internal feedback of the neuron model. Light from a second optical source, when focused onto the optical detector, acts as an optical input.

To demonstrate this behavior, a short train of pulses was applied to the auxiliary source driver, aiming at demonstrating the resonant property of the oscillator. We expect that, if pulse separation is close to the natural interval between spikes, they can have a strong effect on the optical neuron, and that this effect should diminish both by increasing or decreasing the inter-pulse interval. This contrasts with integrators, whose response always is stronger for the shorter pulse interval. In Figure 2b a sequence of two pulse triplets is repeatedly presented. The second triplet in the group is at resonant frequency with the neuron's internal dynamics. The first triplet, which is separated by a shorter interval, indeed fails to elicit a strong response.

Next, two independent spiking circuits were implemented, to investigate their coupling properties. Part of the optical signal from one feedback loop is sent to the other (we will refer to these hereafter as the sending and receiving circuits, respectively). The strength of coupling can be controlled by the amount of focusing of this coupling beam into the receiving detector. In the experiments reported here, coupling is turned on and off by blocking the path of this coupling beam. With this setup, the effect of optical coupling can be shown at different bias levels for the receiving neuron. In Figure 3a, the biasing of the receiving circuit is such that sporadic noise-driven spiking is observed without coupling. When optical coupling is allowed, the effect of the sending neuron's spikes can be seen both in sub-threshold oscillations at the detected signal of the receiving neuron and in an increase frequency of spikes .

4 Perspectives for large spiking neuron arrays

The use of discrete devices is severely limited, and explored here as a proof-of-concept. To be integrated in large scale, this neuron implementation requires a large array of emitters, associated detectors and integrated electronics. These are common building

ESANN'2004 proceedings - European Symposium on Artificial Neural Networks
Bruges (Belgium), 28-30 April 2004, d-side publi., ISBN 2-930307-04-8, pp. 417-422

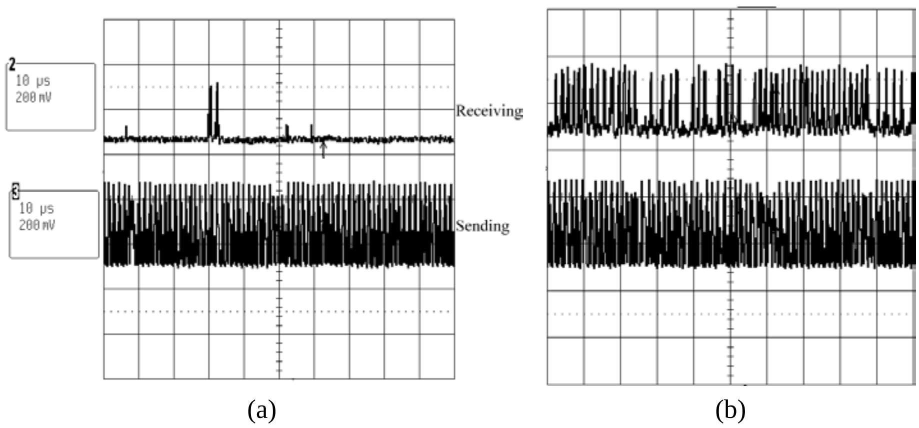

Figure 3: Effect of coupling with the receiving circuit biased to the point of sporadic activity in the absence of coupling. (a) No coupling (b) Coupling induces a larger number of spikes in the receiving neuron.

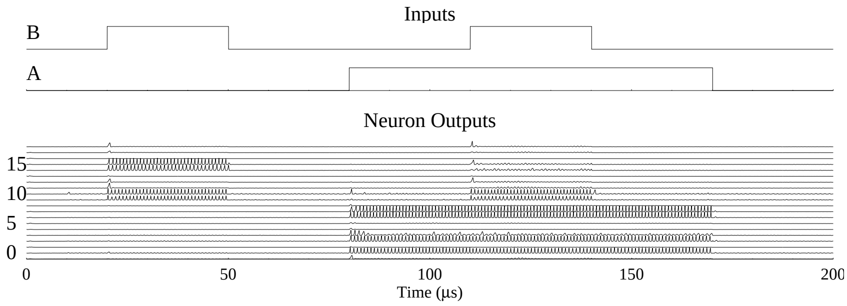

Figure 4: Simulated response of the spiking neurons to discrete variables changing in time. Input peak values 110 mV. Input A connected to neurons 0-9, B connected to neurons 10-19. One half of the interconnections randomly chosen to be set to zero. Remaining connections chosen according to a uniform distribution in the range (0,0.06). Neurons 14 and 15 inhibited by the spiking of neurons 0-9 (and thus do not spike when A and B are high), even though all interconnections are positive.

blocks for the smart pixel array technology. Published results indicate the feasibility of thousands of I/O ports with an output power uniformity of $\pm10\%$ for the VCSEL array [6].

From a computational perspective, we are interested in the time-dependent coupling feature that arises naturally when this type of neuron model is interconnected. In particular, the same input and interconnection strength can have excitatory or inhibitory effect in the receiving neuron, depending on time-of-arrival. This is an interesting possibility for optical implementation, where the representation of bipolar weights is a technological issue. An example simulation of such time-dependent inhibitory effect is seen in Figure 4.

At the architectural level, we are currently evaluating the idea, present in recent works in the area of spiking neural networks [7], of using large networks of fixed, randomly connected spiking neuron as a reservoir of different dynamic responses to the input data, which could than be adaptively combined in a classical supervised learning architecture.

This work presents a dynamic neuron model in physical implementation, using simple linear electronics, low power (mW) optics, and conveniently combining optical and electronic signals. For this approach to be feasible in large scale, it is necessary to incorporate integrated optoelectronic circuits. It is also worth investigating the possibility of exploring other, potentially faster, wavelength modulation effects.

References

[1] N.H. Farhat, D. Psaltis, A. Prata, and E. Pack. Optical implementation of the Hopfield model. *Applied Optics*, 24:1469–1475, 1985.

[2] Y. Frauel, G. Pauliat, A. Villing, and G. Roosen. High-capacity photorefractive neural network implementing a Kohonen topological map. *Applied Optics*, 40(29):5162–5169, October 2001.

[3] J. Goedgebuer, L. Larger, and H.Porte. Chaos in wavelength with a feedback tunable laser diode. *Physical Review E*, 57(3):2795–2798, March 1998.

[4] F.C. Hoppensteadt and E.M. Izhikevich. *Weakly Connected Neural Networks*. Springer, New York, USA, 1997.

[5] B. Linares-Barranco, E. Sánchez-Sinencio, A. Rodríguez-Vázquez, and J.L. Huertas. A CMOS implementation of FitzHugh-Nagumo neuron model. *IEEE Journal of Solid-State Circuits*, 26(7):956–965, July 1991.

[6] Y. Liu, M. Strzelecka, J. Nohava, M.K. Hibbs-Brenner, and E. Towe. Smart-pixel array technology for free-space optical interconnects. *Proceedings of the IEEE*, 88(7):764–768, June 2000.

[7] W. Maass, T. Natschläger, and H. Markram. A model for real-time computation in generic neural microcircuits. In S. Becker, S. Thrun, and K. Obermeyer, editors, *Advances in Neural Information Processing Systems*, volume 15, Cambridge, USA, 2003. MIT Press.

[8] R.FitzHugh. Impulses and physiological states in models of nerve membrane. *Biophysical Journal*, 1:445–466, 1961.

[9] R. Sarpeshkar and M. O'Halloran. Scalable hybrid computation with spikes. *Neural Computation*, 14(9):2003–2038, September 2002.

[10] R. van Rullen and S.J. Thorpe. Rate coding versus temporal order coding: what the retinal ganglion cells tells the visual cortex. *Neural Computation*, 13:1255–1283, 2001.