An Implementation of a Biological Neural Model using Analog-Digital Integrated Circuits

Gary Charles, Christal Gordon and Winser E. Alexander
Department of Electrical and Computer Engineering
North Carolina State University
Raleigh, NC 27695
Email: {gcharle, cgordon2, winser}@ncsu.edu

***Abstract*—Given the trends in reconfigurable hardware systems inspired by biology, we present a hardware implementation of a closed-loop neural system. The hardware implementation focuses on modeling the behavior of two-cells, PD-LP system of a Pyloric Network from a lobster's stomach. This two-cell network emulates, in real-time, a digital representation of interacting neurons whose biological behavior is known. We evaluated the circuit design by varying the circuit values to determine the appropriateness and range of operation of the model. Future development of hardware models will be used to evaluate the feasibility of creating a platform of specialized circuits or an FPNA of biological neural characteristics.**

I. Introduction

Biological neural networks generate patterns of activities that could not have been imagined by studying a single cell in isolation. For instance, the function of the nervous system is a classical example of a complex neural system. The coordinated action of a network of interacting neurons demonstrates the multiplex activities present in the nervous system. One of the major challenges in studying neural networks and their behavior is actually understanding the nature of the *interactions* and *computations* that they carry out. Attempts have been made to understand the interactions between cells by analyzing simple mathematical or computer models. To date, the majority of neural network modeling and implementations have been in software. The development of bio-inspired computer models have extended into the design and implementation of analog-digital VLSI circuits for use in studying biological neural systems.

Analog circuit techniques are the most suitable way of achieving hardware systems capable of modeling neural system behavior. For instance, the function of a neuron can be emulated with a combination of multipliers, current sources and operational amplifiers, and the synapses of a cell can be modeled with floating-gate transistors. Furthermore, interdisciplinary research in the area of neurobiology and circuit design has created hardware neural systems of well-studied species. The heartbeat interneuron of the medicinal leech [1] and the central pattern generator (CPG) circuit in the spinal cord of a lamprey (or eel) [2] are some examples of this work. The hardware development and implementation of biological systems make understanding the interactions and computations of neural systems relatively easier and parameters manageable from a circuit design perspective. With this thought in mind, microelectronic systems targeted for mimicking neural behavior can be assembled to assist researchers in the area of neuroscience and or neurobiology to better analyze the mechanisms which cause cells to function the way they do.

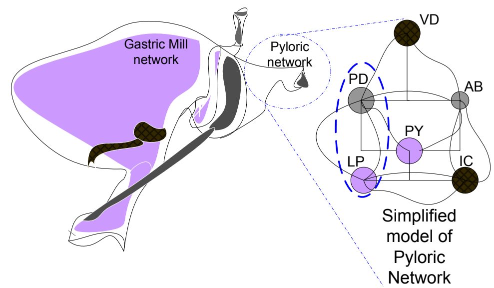


Fig. 1. Stomach of a Lobster (left); Simple Pyloric Network with synaptic connections (right).

This paper presents a circuit model that emulates rhythmic activities using mixed-signals. By changing a few circuit parameters, the desired output response is obtained. The circuit model is designed using analog circuits. The synapses of the circuit model is simulated using an artificial floating-gate transistor to provide control over the amount of current flowing into the system.

II. Biological Neural System

Biological findings suggest that neural systems consist of reconfigurable characteristics similar to reconfigurable logic seen with FPGA platforms. Studies in neurophysiology have shown that neuromodulators can change the processing characteristics of neural networks by affecting the cellular membrane potential, changing synaptic connections (i.e. biological connection) and other parameters. The stomach of a lobster, henceforth stomatogastric ganglion, is a good example of this and is shown in Fig. 1. The biological nervous system is capable of changing its synaptic connections to inhibit and or excite other cells to produce different output responses [3]. The stomatogastric nervous system consists of three individual networks with independent oscillatory behaviors. These individual networks are *oesophageal*, *pyloric* and *gastric* network. Although the oscillatory behaviors are separate from each other, during an event like eating, the lobster's network integrates and coordinates the 3 networks to carry out a task.

A. Biological Basis of the Electronic Neuron

The basis of most biological hardware systems begins with a mathematical description and implementation of a neuron model. The neuron's behavior, presented in this paper, is modeled after a simple integrate-and-fire concept. The circuit will integrate the current for some time, and then will fire off a nerve impulse. After the neuron fires, more current is pumped in until enough charge is built up to fire off another nerve impulse. More specifically, a capacitor, *C1*, from Fig. 2 is used to integrate this current to initiate the process of creating a voltage pulse. The current is integrated into capacitor, *C1*, until the voltage exceeds a certain threshold value. The nFET directly connected to the ground node is biased with a pulse width voltage, V_{pw}. The voltage V_{pw}, determines the wideness of the nerve impulse. The charges are fed back through capacitor *C2* which causes the input voltage to increase even more. Similarly, the role of positive feedback sequence in biology is achieved by voltage-dependent sodium channels. As the voltage inside the cell is increased, more sodium channels open allowing more ions to flow inside the cell. The role of transistors *M1* and *M2* reset the circuit by allowing current to discharge down to ground. Similarly this discharging behavior is played by voltage-dependent potassium channels in neurons allowing ions to flow outside to repolarize the cell. This circuit behavior is illustrated in Fig. 2.

B. Hindmarsh and Rose Neuron Model

This section of the report discusses a software implementation of the Hindmarsh and Rose model [4]. Compared to other neuron models such as the integrate-and-fire neuron, Fitzhugh-Nagumo or Hodgkin-Huxley, the Hindmarsh and Rose, hereafter HR model, has a considerable amount of advantages over the previously mentioned models. For instance, the numerical equations for HR model are much simpler than the Hodgkin-Huxley model. The Hodgkin-Huxley model describes the biological process that creates the nerve pulse which leads to long complicated equations. The HR model captures the overall behavior of the cell and minimizes variable count. Thus requiring less hardware resources and less design complexity. The HR model also presents an accurate description of cell behavior in terms of output frequency to input current relationship than the Fitzhugh-Nagumo and integrate-and-fire models [5]. Although the HR model is a better choice to characterize the bursting behavior of the neuron, the hardware implementation of a two-cell pyloric network is more feasible with a simpler model such as the integrate-and-fire model. This is a first step in understanding how to develop analog hardware design for emulating neural system behavior.

C. Software Implementation of Hindmarsh and Rose Model

The numerical equations for the HR neuron model are obtained from [5] and are shown below:

$$\frac{dx}{dt} = y - ax^3 + bx^2 - z + I \tag{1}$$

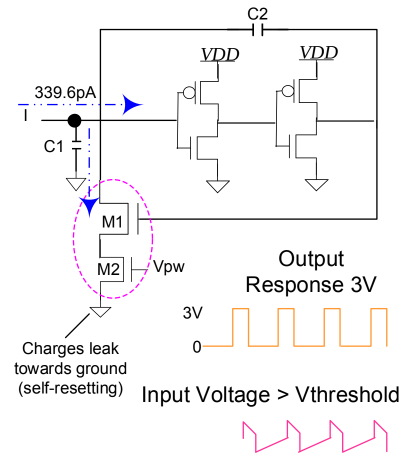


Fig. 2. Hardware implementation of an integrate-and-fire neuron developed by C. Mead [6].

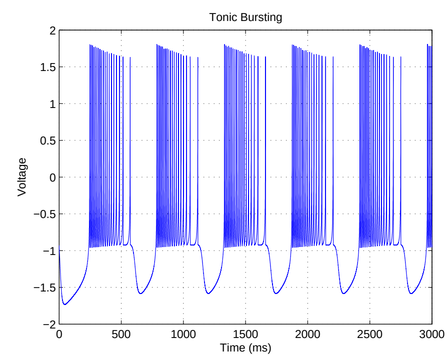


Fig. 3. Simulation using the HR model of a bursting neuron.

$$\frac{dy}{dt} = c - dx^2 - y \tag{2}$$

$$\frac{dz}{dt} = r(s(x - x_1) - z) \tag{3}$$

where,
x: represents the membrane potential
y: represents the recovery current of the neuron
z: adaptation current of neuron
I: the applied current
x_1: equilibrium point of the neuron model without adaptation

The constants for equations (1), (2) and (3) are given in Table I with initial conditions of x_0, y_0 and z_0 to be -0.47, -2.9 and 3.73 respectively. The initial condition values are not required for the operation of the HR model. They were chosen to provide initial values for solving in MATLAB.

TABLE I
COEFFICIENTS USED IN SIMULATION OF HR MODEL

Parameter Constants	Values	Parameter Constants	Values
a	1.0	s	4
b	3.0	r	0.001
c	1.0	x_1	-1.60
d	5.0	I	3

The 3 first order differential systems were solved using an

ODE (ordinary differential equation) solver from MATLAB function library. Fig. 3 shows the output waveform solution of the HR model. The results from implementing the HR neuron model in software illustrates precisely the output pattern that we would like our hardware implementation to produce.

III. Design of Biological Electronic System

Central pattern generator, hereafter CPG, is a neural oscillator located in the spinal cord that is responsible for rhythmic activity in a neural circuit. The CPG consists of a group of neurons that generate a sequence of neural outputs. As a result, these outputs lead to rhythmic behavior in the muscle that is coordinated temporally and spatially. The alternating or oscillatory activity of neural circuits is established by a reciprocal inhibition between pairs of cells. In other words, when one cell is active, the other is inhibited or silent. The following subsections describe the details of the circuits and plots used to illustrate this behavior.

A. Neuron Circuit

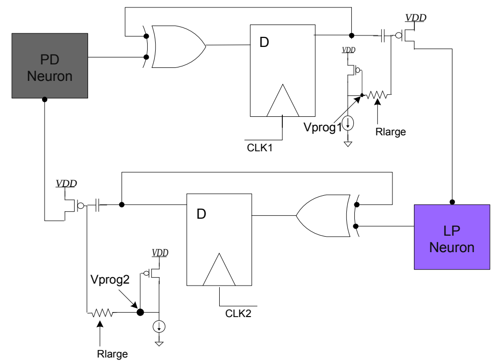
We used the integrate and fire circuit to implement a neuron. The motivation to use an integrate and fire model is primarily due to its simplistic implementation on hardware in terms of complexity. The neuron circuit is composed of a buffer, two nFETs to leak charges to ground, and two capacitors (one for implementing integration by taking in the input current and the other to feed a portion of the output signal back into the input node). The output response of the circuit is shown in Fig. 2

B. Model of a PD-LP Cell

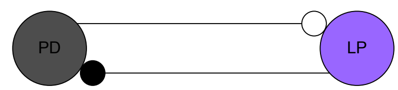
The PD-LP network is a small example of the profuse rhythmic activities that take place in the stomatogastric ganglion of a lobster. Fig. 4(a) is the circuit equivalent of the PD-LP network. Fig. 4(b) is a simplified illustration of the biological two cell being modeled by Fig 4(a). The model system is composed of an integrate and fire neuron circuit that was mentioned in the previous section, an *XOR*-gate, a flip-flop and floating-gate model used for programming the circuits to any given current value. The idea of additional logic such as an *XOR*-gate and flip-flop was to be able to take the single nerve pulse produced by the neuron circuit and demonstrate bursting characteristics seen in Fig. 4(c)-4(d).

C. Artificial Synapse: Floating-gate Model

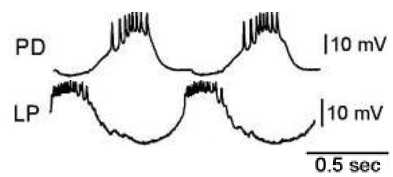
Floating-gate pFETs are widely used to model biological synapses because of their ability to store charges. The artificial synapse implemented with the electronic neuron is a SPICE simulation model provided by Hasler and Serrano[7]. A programmed voltage, V_{prog}, is due to the charge stored on the floating-gate circuit. V_{prog}, is connected to the floating node through a large resistor, R_{Large} in the Giga-ohm range. The value of current injected to the neuron circuit ranges from 150pA to 500pA. Increasing the current would increase the flow of charges. However, the bottom FETs are as important because they are responsible for resetting the system. The rate at which charges leak is related to an influx of current entering the circuit system. If the rate of charges entering the system is much less than the rate of charges leaving, the circuit will not produce a nerve impulse. The reason being, the circuit has to accumulate enough charge to a certain threshold level to produce a digital output response. This is illustrated in Fig. 4(d) and Fig. 5(a)-5(c).



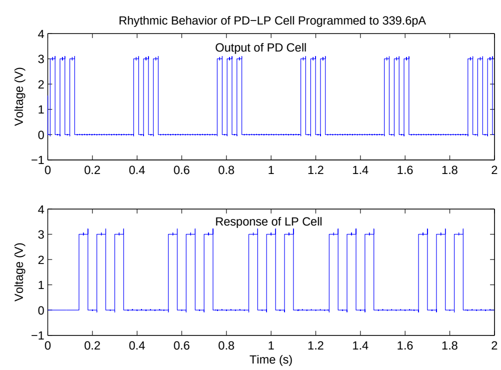
(a) Two Cell Circuit Model (PD-LP network).



(b) Synaptic Connectivity of PD-LP network.



(c) Actual output pattern of PD-LP network from [1].



(d) Digital Response of PD-LP circuit.

Fig. 4. Circuit component of cell network

IV. Simulation Results

The output waveforms were generated using the AMI 0.6μm CMOS process. The circuit model network illustrated similar rhythmic behavior seen in a biological PD-LP network. Although the precise shape of the nerve pulses does not match actual biological pattern as shown in Fig. 4(c), the goal is to illustrate that the behavior of a neural network can be generated with standard integrated mixed-signal circuits. The key factor governing the behavior of the cell depends on the current, I, or amount of charges injected into the floating gate structure. The circuit model behaves precisely as a digital circuit. If the injected current isn't enough to stimulate the cell or rather if the injected current is lower than the activation threshold, then the cell remains at rest. Otherwise, if the injected current is enough to stimulate the cell, then cell activity will occur. The process of adding charges into a floating-gate circuit is hot-electron injection. However, the technique of hot-electron injection is actually performed simply by changing the current levels of the current source. Fowler-Nordheim tunneling technique is carried out by just reducing the current level of the current sources. The pulse width of the signal is controlled through a bias voltage, V_{pw}. It ranges from a value of 250mV to 800mV. The higher this value the more narrow the pulse width of the signal becomes. Each XOR gate takes in two input signals. The output signal from PD or LP model cell serves as one of the input signals to the XOR gate and the output signal from the register is the second input signal shown in Fig. 4(a). The bit sequence produced at the output of the XOR gate will always generate a binary sequence of 01010101... which physically creates the digital pulses that is observed in Fig. 4(d) and Figs. 5(a) through 5(c). The pulse of the neuron circuit is generated in real-time up to 2s.

The waveforms in Figs. 5(a)-5(c) demonstrate the range of output responses that can be obtained when injecting the system to different current levels. Fig. 5(a) is the response from a model LP cell that is at rest (0pA), while the model PD cell has an input current of 339.6pA. Thus, showing that unless charges are injected into the system a nerve pulse will not be produced. The work in 5(b) shows the model LP cell has an input current of 250pA. A single pulse has been produced which alternates with the model PD cell every 3 pulses. One more thing to point out which impacts the firing rate of the model LP cell, is that the bias voltage, V_{pw}, has been increased from 300mV to 350mV. As mentioned before, increasing the bias voltage,V_{pw}, will make the nerve pulses more narrow. As the model LP cell pulses are compared with model PD cell pulses, the model PD pulses are twice as wide. The advantage of having parameters that directly impact the response of the system is such that one can have reasonable control of the behavior of the system.

In Fig. 5(c), the current level was increased to double the previous value to demonstrate how the pulses could be generated even more by the model LP cell. So, for every 5 pulses produced by the model LP cell, the model PD cell produces 3 pulses. Of course the current level for the model PD cell was maintained at 339.6pA while the current for the model LP cell was kept at 500pA. The bias voltage,V_{pw}, was reduced slightly from 350mV to 330mV. The results demonstrates how one is able to control a system that models behavior in biology by injecting current similar to how experimental procedures

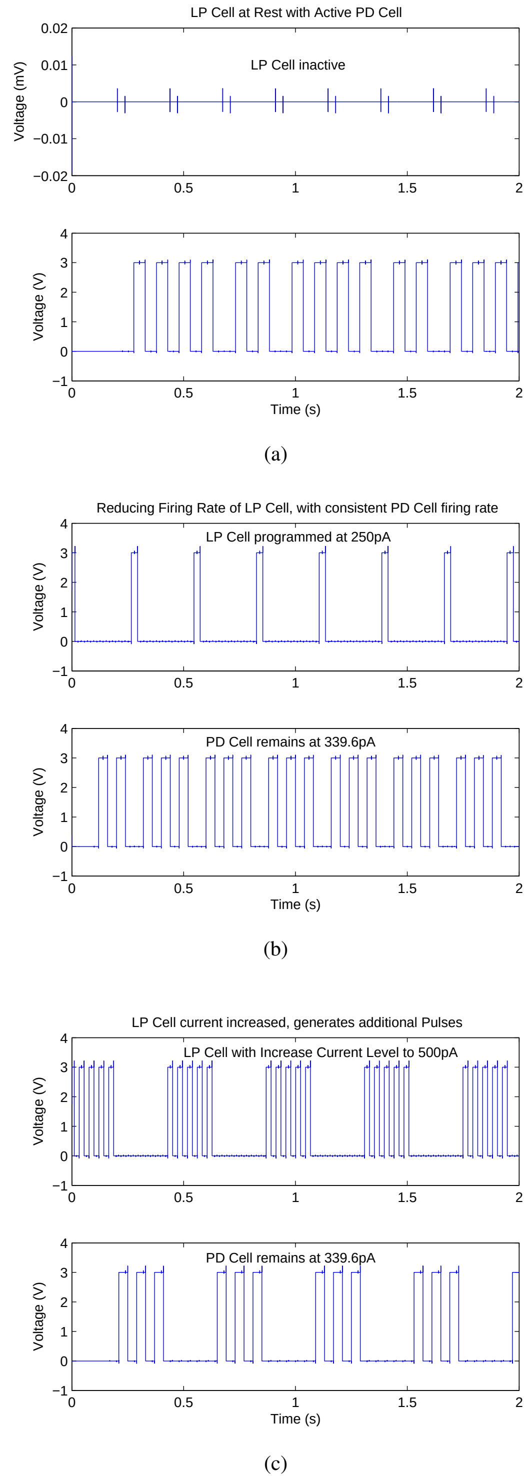


Fig. 5. Results are compared with the Rhythmic Activity from [3]

inject current into real biological cells. The only difference is model cells allow researchers the capability of working with as many cells as they would like with little to almost no difficulty. The purpose of these plots, is to show how neuroscientist who perform biological experiments and conduct research on neural system interaction, can turn to an alternative methodology to study and analyze neural behavior. Similar studies presented in this paper have been done in [3] where researchers study the functions of specific neurons to gain insight into cycle period control in the rhythmic pyloric network.

V. Future Work and Conclusion

A two cell electronic network was designed and simulated using 3V power supply in 0.6μm CMOS technology. The electronic was able to emulate rhythmic behaviors when coupled with another artificial cell in real-time. Since the injected current was fixed at a level that would stimulate the cell, the two cell system was not tested for the minimum current required to produce a pulse. Although accurate systems serve as a potential solution, the accuracy comes at the cost of increased power consumption because of the amount of circuit units included. However, the properties of floating-gate transistors can overcome some of these intrinsic limitations in power consumption and accuracy [8]. The implementation of a floating-gate model in SPICE was used to inject current into the analog design. The focus of this paper was not to develop a new algorithm or custom design to model a neural network. Rather, the focus was to illustrate how mathematical neural models can be used as a framework for implementing neural systems on hardware targeted to emulate a particular cell system.

Recent trends show that Field Programmable Neural Arrays, FPNAs similar to FPGAs, is a fairly new developing area for implementing reconfigurable neural systems in hardware. The aim of the FPNA concept is to essentially develop neural structures that are easy to map directly onto analog/digital hardware. One major tradeoff regarding implementing neural systems in reconfigurable platforms is *area vs. precision* [9]. Since precision is a key feature and highly desirable for understanding neural system behavior, FPNA serve as an excellent method to address the high density issue that leads to area greedy logic. The concept of FPNA comes from a hardware-oriented neural paradigm that led to very efficient implementations of neural systems [10]-[12]. FPNAs are similar to FPGAs in that they are a set of reconfigurable customized circuits. FPNAs are capable of modeling neurons in 3 different forms (1) single complex neuron (2) complex networks of simple neurons or (3) neural systems with moderate complexity in both computational entity and network connectivity [13].

This work will concentrate on studies related closely to implementations targeted towards hardware in general and FPNA as well as FPGA applications. Since the work presented in this paper utilized a basic integrate and fire model, future work will also involve modeling hardware with a more accurate and complex model such as the Hindmarsh and Rose model. Relative to the integrate and fire model, the HR model is complex, but it is less complex than the Hodgkin-Huxley model.

Fig. 6 illustrates the general idea and research focus of interest. Neural systems that are implemented using digital

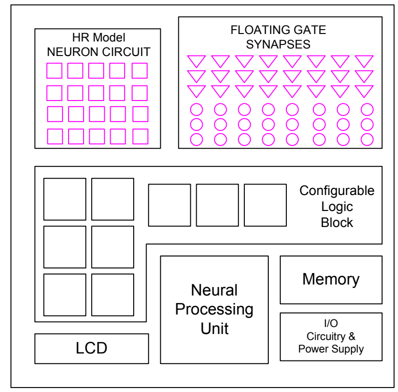


Fig. 6. Block diagram illustrating FPNA concept.

circuits don't necessarily capture all the biological characteristics of a living cell such as refractory period, learning, adaptation just to name a few. By designing and implementing specialized analog circuits to model such characteristics, we will be able to physically understand the electrical behavior of the system in hardware and possibly relate them to real neural system behavior. This in turn will provide better understanding of the electrical processes and interactions within a given neural system. Also, it can serve as an experimental tool for neuroscientist to utilize during their studies. The individual blocks inside Fig. 6 draws from components normally seen with FPGAs and computers. One of our special interests is to investigate and study how neural systems can be reconfigured and implemented with analog and digital hardware that will lead to the future development of FPNAs.

REFERENCES

[1] M. F. Simouni, G. S. Cymbalyuk, M. Q. Sorensen, R. L. Calabrese and S. P. DeWeerth. Development of Hybrid Systems: Interfacing a Silicon Neuron to a Leech Heart Interneuron, *Neural Information Processing Systems 13*. Cambridge, MA. MIT Press, 2000

[2] E. J. Brauer, R. Jung, B. Thompsen, and J. J. Abbas. aVLSI Circuit of Lamprey Unit Pattern Generator. *IEEE*, 1999

[3] A. L. Weaver, S. L. Hooper. Follower Neurons in Lobster (Panulirus interruptus) Pyloric Network Regulate Pacemaker Period in Complementary Ways. *J. Neurophysiology*, 89:1327-1338, 2003

[4] J. L. Hindmarsh, R. M. Rose. A Model of Neuronal Bursting using Three Coupled First Order Differential Equations. *Proceedings of the Royal Society of London*, pp. 87-103, 1984

[5] Y. J. Lee, J. Lee, Y.B. Kim, J. Ayers, A. Volkovskii, A. Selverston, H. Abarbanel, M.I. Rabinovich. Low Power Real Time Electronic Neuron VLSI Design Using Subthreshold Technique. *ISCAS IEEE* 2004

[6] C. Mead. Analog VLSI and Neural Systems. Boston, MA: Addison Wesley, 1989

[7] P. Hasler, G. Serrano. A Floating-Gate DAC Array. IEEE Circuits and Systems ISCAS vol.1 pp 357-360, 2004

[8] S. Bridges, M. Figueroa, D. Hsu and C. Diorio. A Reconfigurable VLSI Learning Array, *IEEE Proceedings of ESSCIRC*, pp 117-120, Grenoble, France 2005

[9] Omondi A. R, and J.C. Rajapakse (Eds). FPGA Implementations of Neural Networks. Springer: Netherlands, 2006

[10] B. Girau. FPNA: Interaction between FPGA and neural computation. *Int. Journal on Neural Systems*, 10(3):243-259, 2000

[11] B. Girau. On-Chip Learning of FPGA-inspired neural nets. In *Proc. IJCNN. IEEE*, 2001

[12] B. Girau. Dependencies of composite connections in Field Programmable Neural Arrays. Research Port NC-TR-99-047, NeuroCOLT, Royal Holloway, University of London, 1999

[13] E. Farquhar, C. Gordon, P. Hasler. A Field Programmable Neural Array. *ISCAS IEEE*, 2006

[14] B. Girau. Neural Networks on FPGAs: A Survey. In *Proc*. Neural Computation, 2000