A Novel Neural Oscillator and Its Implementation in Analog VLSI

Qiang Luo   John G. Harris
Computational Neuro-Engineering Laboratory
University of Florida
453 Engineering Bldg., Bldg. 33
Gainesville, FL 32611-6130

ABSTRACT

This paper presents a novel neural oscillator model that is inspired by biological oscillation models and is easily implemented in subthreshold analog CMOS VLSI. The proposed model uses local coupling among neuron units. Synchrony and information propagation are demonstrated in chains and rings of the oscillators.

1. INTRODUCTION

Using neural oscillations to encode temporal correlation has received considerable interest in the literature [1, 2]. Many researchers believe that neural oscillations are triggered by sensory stimulation and that these oscillations are used in subsequent computation. The simplest models hold that synchronous oscillations occur across an extended brain region if the stimulus constitutes a coherent object. A recent example of this type of model is Terman and Wang's LEGION model [3]. More sophisticated models of brain activity, such as Freeman's olfactory model propose chaotic networks of local oscillators for associative memories and other computations [4]. There are too many examples of neurodynamical models in the literature to exhaustively list them all but a common element in many of these models is a simple oscillator connected in a prescribed topology to achieve some sort of computation. Much work has been done on the numerical analysis of different oscillator models and on difficulties in their digital numerical simulation. Here, we propose to use analog VLSI to build efficient, real-time simulations of a whole host of different neural dynamic models.

There are already examples of VLSI neural oscillators in the literature including work in our lab involving networks of Chua oscillators [5, 6] and a VLSI implementation of Freeman's model [7]. However, these circuits and others in the literature [3, 8] require complex or nonhomogenous oscillators that complicate the VLSI implementation. Our goal in this paper is to design the simplest local oscillator that can still be used in neurodynamics experiments for computation.

In section 2, we describe our single neural oscillator model. In section 3, we present the synchrony and information propagation in chains and rings topologies of the neural oscillators. Finally, in section 4, we present the simulated results of the VLSI implementation.

2. SINGLE NEURAL OSCILLATOR MODEL

The relation among neurons of the central nervous system can be considered to be a neuron link system [9]. A simple link consists of one excitatory neuron and one inhibitory neuron, which forms a closed loop. Among the simple links a variety of median neurons may form more complicated loops. Research on short-term memory [9] has shown that there exists oscillation among these neuron loops in the brain. A simple neuron closed loop oscillator may look like that shown in Figure 1. Based on this topology, we propose a novel neural oscillator model.

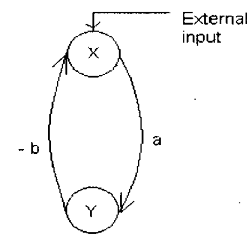


Figure 1 The topology of a single neural oscillator. Neuron X is an excitatory neuron and neuron Y is an inhibitory neuron. a is the synaptic link weight from neuron X to neuron Y. $-b$ is the synaptic weight from neuron Y to neuron X. Both a and b are positive values.

In Figure 1, neuron X is an excitatory neuron and neuron Y is an inhibitory neuron. a is the synaptic link weight from neuron X to neuron Y. $-b$ is the synaptic weight from neuron Y to neuron X. Both a and b are positive values. The positive link from neuron X to neuron Y indicates neuron X excites neuron Y. Similarly, the negative link from neuron Y to neuron X indicates neuron Y inhibits neuron X. The single neuron model is depicted in Figure 2.

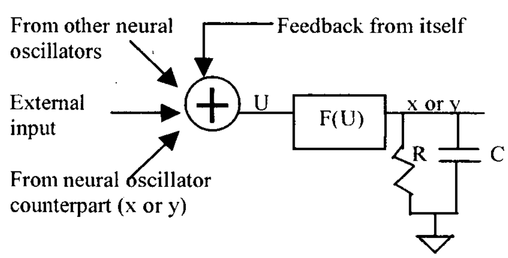


Figure 2 The single neuron model.

The sum unit in the single neuron mod ... nts the summation characteristics of the nervo ... [9]. The

0-7803-6685-9/01/$10.00©2001 IEEE

stimulation from different sources such as the external input, neural oscillator counterparts, other neural oscillator outputs or the feedback from the neuron itself will be added together. The total value of stimulation after the summation is named U. This sum will be input to a nonlinear function F(U) to produce the output of the neuron. x and y in Figure 2 are the output of neuron X and neuron Y in Figure 1, respectively. R and C in Figure 2 denote the resistance and capacitance of neuron membrane. The stimuli have the characteristics of voltage. The nonlinear function F(U) works like a voltage-to-current converter. The performance of the nonlinear function F(U) determines the states of the neuron and is described by a sigmoid function

$$F(U) = I_b \tanh(g \cdot U - \theta) \qquad (1)$$

where I_b is the bias current of the voltage-to-current converter, g is the gain of the neuron and θ is the threshold of the neuron.

Based on these models and Kirchoff current laws, the neural oscillator model is described by the following differential equations.

$$\begin{cases} C\dfrac{dx(t)}{dt} = -\dfrac{x(t)}{R} + I_b \tanh[g \cdot (x - by + E + S_x - \theta_x)] \\ C\dfrac{dy(t)}{dt} = -\dfrac{y(t)}{R} + I_b \tanh[g \cdot (ax + S_y - \theta_y)] \end{cases} \qquad (2)$$

Where E denotes the external stimuli, S_x and S_y denote the output of other neural oscillators, θ_x and θ_y are the threshold of neuron X and neuron Y respectively. In the model, we assume the excitatory neurons and inhibitory neurons have the same membrane resistance and capacitance. We also assume the sigmoid functions of these two kinds of neurons have the same gain and bias. In addition, there exists positive feedback in the excitatory neurons, which is required for oscillation.

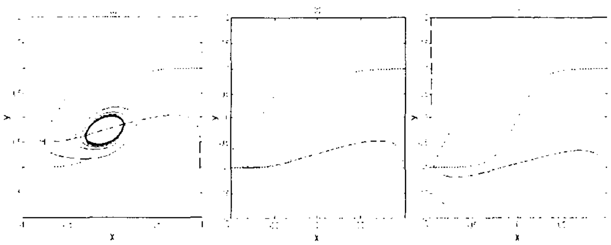
When the input to the excitatory neuron is larger than the threshold of the neuron, the excitatory neuron will give the inhibitory neuron a positive stimulus, which causes the inhibitory neuron to increase its inhibitory stimulus to the excitatory neuron. The increase of this inhibitory input will cause the excitatory neuron to decrease or even lose excitation. Meanwhile the positive feedback of the excitatory neuron tries to push the excitatory neuron into excitatory state. As time goes on, when the accumulation of positive stimulation increases high enough above threshold, the excitatory neuron becomes excited again and the same course of events repeats. This is the application of accumulation on temporal space of the nervous system [9]. The neural oscillator thus works as a relaxation oscillator. When S_x and S_y are zero, the nullclines of the neural oscillator in equation (2) are

$$y = \frac{1}{b}\left(x - \frac{\tanh^{-1}\left(\dfrac{x}{I_b \cdot R}\right)}{g} + E - \theta_x \right) \qquad (3)$$

$$y = I_b \cdot R \cdot \tanh(g \cdot (a \cdot x - \theta_y)) \qquad (4)$$

When g=2, a=2, b=1, $\theta_x = 0.72$, $\theta_y = 0$, E=0.5, $I_b \cdot R = 1$, the nullclines in equation (3-4) are shown in Figure 3(a). Keeping all the other parameters unchanged and letting E=0 (external stimulation is 0) and E=-0.2 (negative input/inhibitory input), the resulting nullclines are shown in Figure 3(b) and Figure 3(c).

It is clear that equation (2) defines a typical relaxation oscillator. When E>0, there is only one intersection point between the two nullclines and the oscillator produces a stable periodic orbit. When E=0, the nullcline of equation (3) starts to intersect the nullcline of equation (4) at a stable fixed point. This is the critical state. As E becomes negative, the oscillator quits from the active state and the system converges to a stable point. Examples of the trajectories in phase space with external input E=0.5, E=0 and E=-0.2 are also shown in Figure 3. The initial point is at (-0.5 0.5). The simulations were numerically solved with the fourth-order Runge-Kutta method. It is clear that a limit cycle is generated when the external input is greater than 0 and the system reaches a stable point when the external input is zero or less.



(a) (b) (c)

Figure 3 Nullclines and trajectory of a single neural oscillator shown in phase space. Dash line is the nullcline of equation (3). Dot line is the nullcline of equation (4). The solid lines in Figure (a), (b), (c) are the trajectories in phase space for E=0.5, E=0, and E=-0.2.

Finally, it should be pointed out that there exist ranges for the parameters in the single neuron model. We tried to select a good set of parameters that will fit the parameters of a VLSI circuit and facilitate the design. The set of parameters discussed above is one such set and they are selected to build circuits.

3. SIMPLE NETWORKS OF NEURAL OSCILLATORS

The single neural oscillators are connected together to construct a chain of N oscillators (Figure 4). Each oscillator is connected to its neighbors by coupling between excitatory neurons and between inhibitory neurons. W_e denotes the synaptic connection weights between excitatory neurons and W_i denotes the synaptic connection weights between inhibitory neurons. The effects of neighbor neural oscillators are described by

$$S_x(k) = W_e(k,k-1)\cdot x(k-1) + W_e(k,k+1)\cdot x(k+1) \qquad (5a)$$

$$S_y(k) = W_i(k,k-1)\cdot y(k-1) + W_i(k,k+1)\cdot y(k+1) \qquad (5b)$$

Assume that all the W_e's have the same value and that all the W_i's have the same value. For the neurons at the head and tail, let the weights be doubled so that the weights are balanced through the chain. We found that with uniform external input and random initial values for each oscillator, the chain is synchronized after an initial period of phase transition. Figure 5(a) presents a simulation with N=10 oscillators. Homogeneous inputs were used as the external stimulation to the neural oscillators. W_e=0.3, W_i=0.05. From the figure we can see that when the system is in synchrony, $x_i=x_j$ (i, j=1, 2, ... , N). Because of the equal weights to each oscillator, $dx_i/dt = dx_j/dt$. Therefore, the system will keep the stability of the synchronized solution.

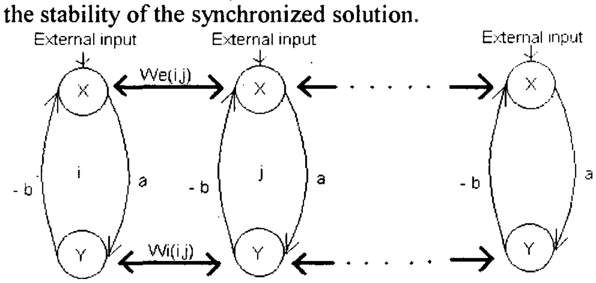
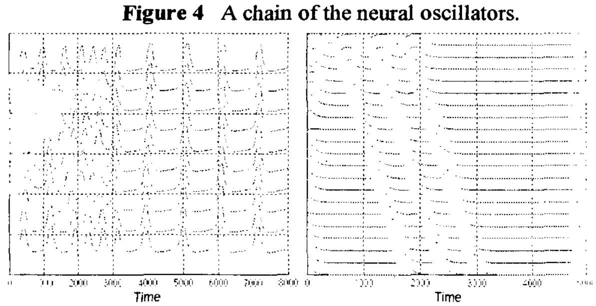


Figure 4 A chain of the neural oscillators.



(a) (b)

Figure 5 (a) Synchrony in a chain of 10 neural oscillators with homogeneous inputs of 0.5. The initial values of excitatory and inhibitory neurons are set randomly. W_e=0.3, W_i=0.05. 8000 integration steps are simulated. (b) Information propagation in a chain of 20 oscillators. External stimuli of E=0.2 was input for 2000 integration steps to the first oscillator (the top one). Then it was cancelled. The information was propagated through the chain.

Cohen [10] and Wang [11] also achieved synchrony in their neural networks but our model is simpler and uses a unique neuron model with the parameters decided by circuit implementation. In addition, the connections between both excitatory and inhibitory neurons are taken into consideration, which covers the single connection case [11] and provides potential control and application to the neural networks.

For non-homogeneous inputs, the propagation of information in a chain of oscillators is studied. Stimulation to the first neural oscillator was given for some time. Then it was removed. The oscillation propagated from the first oscillator to its neighbor, then to its neighbor's neighbor, and so on. A simulation result is shown in Figure 5(b) with 20 oscillators in a chain. All the parameters are the same as in Figure 5(a), except that there is only one stimulus to the first oscillator and it lasts for 2000 integration steps.

Moreover, a ring of neural oscillators is formed by connecting the first and last oscillators in Figure 4 together. The connection weights are the same as in equation 5. Synchrony and propagation can also be found in the ring of the oscillators.

4. CIRCUIT REALIZATION

The neural oscillator model is implemented in analog CMOS VLSI. A precise implementation of the tanh function in the neuron model will require a lot of components in an above threshold CMOS implementation. However it can be easily realized with a transconductance amplifier in the subthreshold region. Working below threshold will further save power consumption. The nonlinear unit F(U) in Figure 2 is characterized by a wide range transconductance amplifier (transamp) working in subthreshold region. Let V_{i+} and V_{i-} denote the input signals to the non-inverse and inverse ports of the amplifier respectively. Let I_o and I_b denote the output current and the biasing current providing the working current for the transconductance amplifier respectively. It is shown that [12] the output current satisfies

$$I_o = I_b \cdot \tanh\frac{\kappa(V_{i+} - V_{i-})}{2} \qquad (6)$$

where κ is the parameter denoting the effect of charges from the ionized donors or acceptors in the substrate under the gate reducing the effectiveness of the gate at controlling the barrier energy.

A complete neural oscillator circuit schematic is shown in Figure 6. A summing block is needed as a voltage adder. Since an opamp adder is not an ideal candidate, we proposed a voltage adder that consists of several transamps that work in the subthreshold region. The addition/subtraction is implemented within the linear regions. Diode degeneration is used to increase the linear region of the transamps. The parameters (a, b, g, etc) of the model are realized by controlling the bias voltage of the transamps. In addition, since

$$\tanh(z-\theta) = -\tanh(\theta - z) \qquad (7)$$

(here z and θ denote the input signal and threshold voltage to a nonlinear unit respectively), we can simply reverse the inputs to the nonlinear unit to get the inverse output. This can easily realize the subtraction in the model. There are 11 transistors in a wide-range transamp and 7 transistors in a simple transamp. The whole circuit is composed of transamps and capacitors, which makes the full oscillator very small. In addition, the gain of wide range transamps and the resistance of simple transamps can be easily controlled by bias voltages, which makes the circuits flexible. SPICE simulation results are shown in figure 7 for a 1.6um CMOS process.

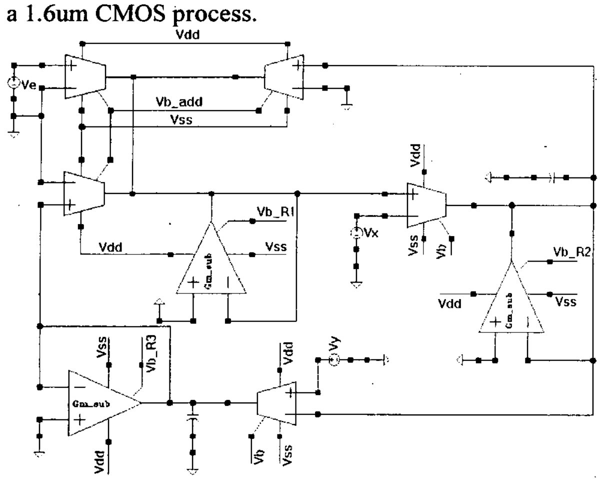


Figure 6 The schematic of a single oscillator. The triangular units denote simple transamps. The polyangular units denote wide range transamps. Ve denotes the external input. Vx and Vy denote the threshold voltage of excitatory and inhibitory neuron respectively.

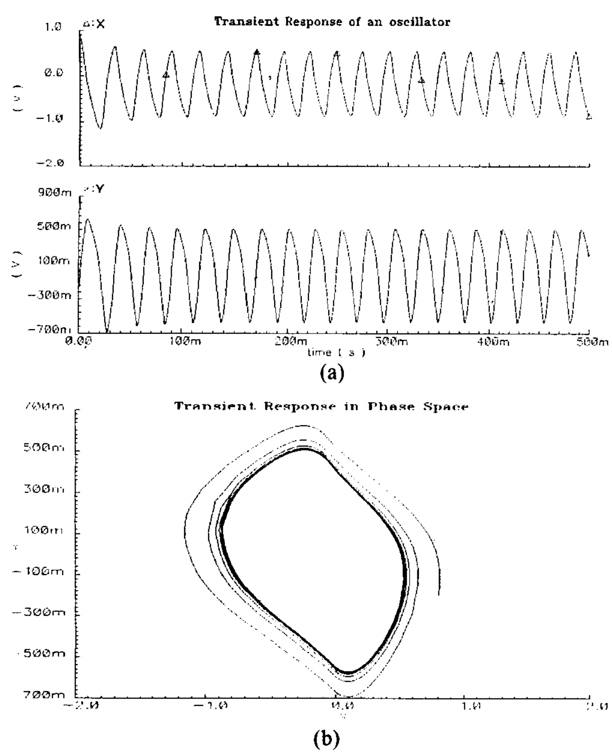


Figure 7 Simulation results of the circuit oscillation behavior. (a) is the transient response of an oscillator. (b) illustrates the outputs of neuron units in phase space. External input is 50mV. Vdd=+1.5V, Vss=-1.5V.

5. CONCLUSION

This paper presents a novel neural oscillator model that is inspired by biological phenomenon and designed for subthreshold circuit implementation. The model parameters are decided according to the circuit parameters and is easy to be implemented with mixed mode, sub-threshold, VLSI technology. The built-up oscillator is input controllable and exhibits the characteristics of synchrony under homogeneous input in a chain or ring of the oscillators. These are in agreement with some of the existing neural oscillators [3, 4, 11]. Information propagation (nonhomogeneous input) is also demonstrated in a chain network of oscillators. Further research will be focused on the information storage and associative memory in the neural oscillator networks.

REFERENCE

[1] W. Singer and C. Gray, "Visual feature integration and the temporal correlation hypothesis", Ann. Rev. Neurosci., vol. 18, pp. 555-586, 1995

[2] A. Keil, M. M. Mueller, M. J. Ray, T. Gruber, and T. Elbert, "Human gamma band activity and perception of a Gestalt", J. Neurosci., vol. 19, pp. 7152-7161, 1999

[3] David Terman, D. L. Wang, "Global competition and local cooperation in a network of neural", Physica D. 81, pp.148-176, 1995.

[4] Walter J. Freeman, Yong Yao, Brian Burke, "Central pattern generating and recognizing in olfactory bulb: A correlation learning rule", Neural Networks, vol. 1, pp. 227-288, 1988

[5] John.E. Neeley, Charles.H. Overman, and John.G. Harris, " Synchronization of subthreshold-CMOS chaotic oscillators", In IEEE International Symposium on Circuits and Systems, pp. 493-496, Monterey, CA, May 1998.

[6] John .E. Neeley and John.G. Harris, "A subthreshold CMOS chaotic oscillator", In IEEE International Symposium on Circuits and Systems, pp. 269-271, Atlanta, GA, May 1996.

[7] Vitor M. G. Tavares, Jose C. Principe, John G. Harris, "A silicon olfactory bulb oscillator", In IEEE International Symposium on Circuits and Systems, Geneva, Switzerland, May 2000

[8] Joe Eisenberg, W. Freeman, B. Burke, "Hardware architecture of a neural network model simulating pattern recognition by the olfactory bulb", Neural Networks, 2, pp. 315-325, 1989

[9] Gary U. Thibodeau, Kevin T. Patton, "Anatomy and Physiology (3rd edition)", St. Louis, MO: Mosby, c1996

[10] A.H. Cohen, P. J. Holmes, R. H. Rand, "The nature of coupling between segmental oscillators of the lamprey spinal generator for locomotion: A mathematical model", J. Math. Biol., vol. 13, pp. 345-369, 1982

[11] D. L. Wang, "Emergent synchrony in locally coupled neural oscillators", IEEE trans. on neural networks, vol. 6, no. 4, pp. 941-948, 1995

[12] Carver Mead, "Analog VLSI and neural systems", Addison-wesley publishing company, 1989.