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HINDMARSH–ROSE NEURON MODEL USING TWO-COUPLED BIOLOGICAL NETWORKS WITHOUT DIGITAL MULTIPLIERS

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ABSTRACT:

The efficient modeling, simulation, and implementation of biological neural networks are key objectives of the neuromorphic research field, leading to potential applications, such as assisting the search for new solutions to cure brain diseases, improved performance of robots, and the fundamental study of neural network behavior. This brief proposes modified biological Hindmarsh–Rose (HR) neuron model that is more suited for efficient implementation on digital platforms. Simulation results show that the model can reproduce the desired behaviors of the neuron. The proposed model is investigated, in terms of digital implementation feasibility and cost, targeting a low-cost hardware implementation. Hardware implementation on a field-programmable gate array shows that the modified model mimics the biological behavior of different types of neurons, with higher performance and considerably lowers hardware overhead cost compared with the original HR model.

KEYWORDS: Field-Programmable Gate Array(FPGA), Spiking Neural Network(SNN),Hindmarsh–Rose(HR)Neuron Model.

I. INTRODUCTION The increased fundamental understanding of neural network architectures in the brain is one of the motivations of exploring hardware implementations of neuronal models [1]–[10]. In order to mimic and hence understand aspects of brain behavior, one may consider a system that includes a largenumber of primary building blocks and the basic signaling unit of the nervous system, neurons, which are connected to each other in an intricate pattern in the brain [11].For the simulation and implementation of these complex architectures, mathematical modeling of neural dynamics and spiking-neural-network mechanisms have been used in the analysis of neuron behavior [12]. In this case, the behavior of single neuron can be explained and analyzed by mathematical equations with different levels of biological accuracy. A biological neuron is a dynamical system that produces dynamical behaviors, which can be described by a set of differential equations [13]–[22]. Several biological neuron models have been reported. The most successful and widely used neuron model, the Hodgkin–Huxley (HH) model [23], has been described. The ionic mechanism and electrical current on the membrane surface are taken into consideration in this model. After that, the FitzHugh–Nagumo (FHN) neuron model, which is the simplified version of theHHneuronmodel,was proposed [24]. The Morris–Lecar neuron model is a conductance-based model, and it was proposed [25] in order to describe oscillations in barnacle giant muscle fiber and is thus biologically significant. The Hindmarsh–Rose (HR) neuron model [26] displays several neuronal behaviors and an accurate output-frequency-to-input-current relationship. In addition to having a simple mathematical description, theIzhikevich neuron model [11] includes very rich neuronal dynamics compared with the HH neuron model. In all types of neuron models, there are two main mechanisms: First, there are the conductance-based models with high biological precision and high computational cost, such as theHHmodel, and second, there are the spiking-based models, which describe the temporal behavior of the cortical spikes or spike timing, such as the Izhikevich model. Consequently, there is a tradeoff between model accuracy and its computational complexity. On the other hand, the main advantage of the HR neuron model is that it is a very simple mathematical neuron model, which describes the thalamic neurons of the brain. A previous software-based work analyzed synchronized networks using neuronal models and global couplings [14]–[17], thus motivating the need for an efficient hardware implementation. This desired feature provides the possibility of testing and understanding biological neuron experiments. The implementation of these neuron models on different platforms has been studied such that both analog and digital implementations have been considered. Recently, reconfigurable digital platforms have been used to performed nervous system models [1]–[5],[12], [18]–[20]. Field-programmable gate arrays (FPGAs) are generic programmable digital devices that were used for the implementation of the adaptive-exponential, Izhikevich, FHN,HR, and Morris–Lecar neuron models [1]–[5], [12], [18]–[20]. Although digital computation consumes more silicon area and power per function in comparison with an analog realization, its development time is considerably lower and is robust against power supply fluctuations and thermal noise. The main objective of this brief is to achieve a low hardware overhead and a highly efficient realization of two coupled neurons for use in major neural networks as a main block. This brief presents a significantly simplified implementation of the HR neuron model.The rest of this brief is organized as follows. Section II presents the dynamics of the HR model, while in Section III, the proposed model is investigated. Section IV presents the dynamical behaviors of synaptic coupling and synchronization. The design and hardware implementation are discussed in Section V. Section VI presents the implementation results. Finally, Section VII concludes this brief. The equations of the HR model describe the behavior of the neuronal action potential. The HR neuron model cans be described by three coupled differential equations as follows

$$\begin{cases} \frac{dx}{dt} = y - f(x) - z + I_{\text{app}} \\ \frac{dy}{dt} = g(x) - y \\ \frac{dz}{dt} = r\,(h(x) - z) \end{cases} \quad (1)$$

where

$$\begin{cases} f(x) = x^3 - 3x^2 \\ g(x) = 1 - 5x^2 \\ h(x) = 4\left(x + \frac{8}{5}\right). \end{cases} \quad (2)$$

Here, x is the membrane potential, y is the spiking variable (also known as the recovery current), and z is the bursting variable (also known as the adaptation current). Also, Iapp is the applied neuron current, and in the presence of spiking behaviors, r controls the spiking frequency, whereas in the case of bursting, r affects the number of spikes per burst.

II. DYNAMICS OF THE HR MODEL To explain the transition from resting state to spiking state(bifurcation), the interactions of the two null clines play an important role [19], [27], [28].As mentioned, the HR neuron model has three coupled equations. On the other hand, based on (1), the z variable of the HR equations is assumed to be a constant value during this analysis, as it is slow when compared to the x and y variables. Thus, this change in the 2-D HR model results in a more accurate frequency–current relationship. In general, two modes of operation can be displayed by the HR neuron model: 1) spiking and 2) bursting. In the spiking mode, it is assumed that the bursting variables are equal to zero, and it is a constant value during this analysis. This means that, in spiking mode, the slow z variable remains in a stable equilibrium, and the system is converted to a 2-Dmodel. In this way, the frequency depends on the value of Iapp,and the bursting controller parameter r cannot affect the spiking rate

III. HR PIECEWISE LINEAR MODEL In this section, the proposed modification to the original model is presented. The main motivation for these modifications is the implementation cost of the modified design. The membrane potential equation of the HR model can be rewritten, Where a=1.394, b=0.189, c=1.40, d=1.42, and mi, 0<I piecewise linear(HRPWL) neuron models. Fig.1(b) shows that the g(x) can be approximated by five PWL segments (shown with red dotted lines), re presenting linear and nonlinear terms in the equation. The mean absolute error (MAE) is another useful measure widely used in model evaluations. Also, MAE measures how far away predicted values are from observed values and is one of a number of ways to compare forecasts with their eventual outcomes [19]. MAE is a linear score, which means that all the individual differences are weighted equally on the average. As the name suggests, MAE is an average of the absolute errors |ei| = |xpropi –xorigi|, where xpropi is the prediction and xorigi is the true value. In this brief, MAE is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |e_i|. \qquad (3)$$

IV. SYNAPTIC COUPLING MODEL In this section, the dynamical behaviors of two coupled HR neurons are presented. Accordingly, we can see the various dynamical behaviors as the current stimulus of the presynaptic neuron, the parameter r that controls the spiking frequency, and the conductance coefficient of the synaptic terminal are varied. The synaptic terminal acts as an active gate, and when the presynaptic voltage level reaches its threshold value, voltage transmission can occur. This state depends on the input stimulus, the coupling of the neurons with the same potentials (xpre = xpost), and when two coupled neurons are synchronized. As mentioned previously, the synchronization effects of coupled neurons are significant for the processing of biological signals and play significant roles in the elucidation of diseases, such as Parkinson’s disease, essential tremor, and epilepsy. Consequently, by the appropriate selection of the input current stimulus and synaptic conductance coefficient, the synchronization effects can be controlled.

V. DESIGN AND HARDWARE IMPLEMENTATION This section presents the hardware implementation structure for the proposed model. In order to obtain an improved comparison in the number of used multipliers between the original and proposed models, As the first step, it is necessary to discretize equations for both models; therefore, we utilize the Euler method. The second step is the bit-width determination of the hardware functional units. The span of the membrane potential is −2 to 2V, and the minimum bits for implementing the membrane potentials are 3 b. In the bitwidth determination, if the maximum logic shifts to the right or left are not considered, then overflow can occur. To avoid any overflow and also increasing accuracy of the calculations, a bit width of 20 that consists of 8 b for the integer part and 12 b for the fraction is considered

VI.CONCLUSION A multiplier less piecewise linear model based on the HR model, targeting a low-cost digital implementation, has been presented. Simulation results and hardware realization show that the proposed model has acceptable error and is suitable for digital implementation. This proposed model has lower computational and hardware costs compared with the original neuron model. This system is conveniently implemented on FPGA. This hardware is used to demonstrate different dynamics of the HR neuron model, depending on the parameter values and current stimulus, producing different patterns of spiking activity with minimal computational error

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