ECG Encoding with AdEx Neuron

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***Abstract*—Biomedical signals are used to realize the underlying physiological mechanisms of specific biological systems or events. An electrocardiogram is one such biomedical signal, which records the electrical signal from the heart to check for different heart conditions. Our idea is to use digital neurons inspired by neuromorphic technology to encode the ECG waveform in the form of spikes. We used the Adaptive exponential integrate-and-fire (AdEx) neuron model for building our neural encoder. Two additional constants are introduced for hardware reduction. As well as the exponential function had been approximated by a combination of integral and Taylor series methods. Using our neuron, we were successfully able to produce encoded spikes for P, Q, R, S, and T waves in the ECG signal. The final implementation of the neuron consumes 241 LUTs.**

Keywords— Adex, ECG, SNN, LUTs, RTL

I. INTRODUCTION

Biomedical signal processing allows real-time monitoring which can lead to better management of chronic diseases, earlier detection of adverse events such as heart attacks and strokes, and earlier diagnosis of other diseases. ECG is one such biomedical signal which can be used to analyze heart arrhythmia. Some of the important characteristics of ECG signal such as P-wave, QRS - complex, ST - segment, T – wave is required to be analyzed to assess different cases of arrhythmia.

Biological neuron models, also known as spiking neuron models, are mathematical descriptions of the properties of certain cells in the nervous system that generate sharp electrical potentials across their cell membrane, roughly one millisecond in duration, called action potentials or spikes. There are multiple varieties of neuron models for implementing an encoder. A few such models are Hodgkin - Huxley, Leaky integrate and fire, Adaptive integrate and fire, Adaptive exponential integrate-and-fire (AdEx) and Izhikevich. We preferred to take the AdEx neuron model because of its lower computational complexity and close mimicking of real neuron behavior.

II. DIGITAL IMPLEMENTATION OF ADEX NEURON

Differential equation representing AdEx neuron behaviour,

$$\frac{Cd}{dt}v = -g_L(v - E_L) + g_L \Delta T exp\left(\frac{v - v_t}{\Delta T}\right) + I - \omega$$

$$\frac{\tau_\omega d}{dt}\omega = a(v - E_L) - \omega$$

If V > V_max then $v \rightarrow v_r$ & $\omega \rightarrow \omega + b$
(where, Vr = EL & 0 mV < Vmax > 30 mV)

In order to build an efficient digital hardware for the above differential equations an optimal and practical approximation has been considered for the exponential functions in the equations. So, we came up with an approximation method consists of techniques from integral and tailor series approximations.

Differential exponent with Taylor series approximation

$$e^{x+\Delta x} = e^x e^{\Delta x}$$

Approximating the $e^{\Delta x}$ using Taylor series, such that the final equation will look like,

$$\boldsymbol{e^{x+\Delta x}} = e^x\left(1 + \Delta x + \frac{(\Delta x)^2}{2!}\right)$$

Digital representation of above approximation,

$$\boldsymbol{e_n} = e_{n-1}\left(1 + \Delta x + \frac{(\Delta x)^2}{2!}\right) \quad \text{were, } e_n = e^{V+\Delta V}$$

A detailed analysis of the differential equation in MATLAB reveals that the variables V and Win the difference equation works in mV and nV range respectively. The hardware requirement in the nV range has been eliminated by bringing the voltage region of the variable W into mV by incorporating two additional constants without affecting the functionality and characteristics of the differential equation.

The above representation of exponential function in the AdEx model makes it more accurate when compared with that in [1] and less hardware hungry when compared with that in [2]. The error analysis of the encoded signal has been done using MATLAB and the same is presented in Fig. 1 which shows a significant reduction in error for the proposed model.

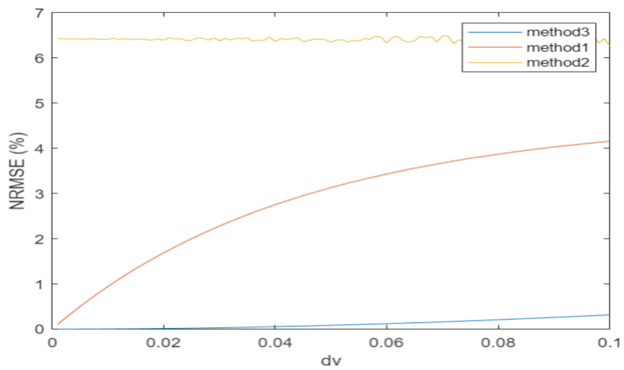

Fig.1: Comparison of normalized root mean square error in hardware implementation of exponential function by the proposed AdEx model given as method 3 with that by [1] given as method1 and by [2] given as method 2 inside box.

Optimised difference equation for digital hardware

$$W_{n+1} = W_n + \left(\frac{dt}{\tau_\omega}\right) aK1(V_n - E_L) - \left(\frac{dt}{\tau_\omega}\right) W_n$$

$$V_{n+1} = V_n - \left(\frac{dt}{C}\right) g_L V_n + \left(\frac{dt}{C}\right) g_L E_L + E + \frac{\left(\frac{dt}{C}\right) I}{K2} - \left(\frac{dt}{CK1}\right) W_n$$

$$\mathrm{E} = \left(\frac{\mathrm{dt}}{\mathrm{C}}\right) \mathrm{g_L} \Delta \mathrm{Te_n}$$

$$e_{n+1} = e_n\left(1+\frac{dv}{\Delta T}+\frac{dv^2}{\Delta T^2}\right)$$

Here K1 and K 2 are the two additional constants introduced, by appropriately adjusting which, the range of values of the variables W and I can be properly set.

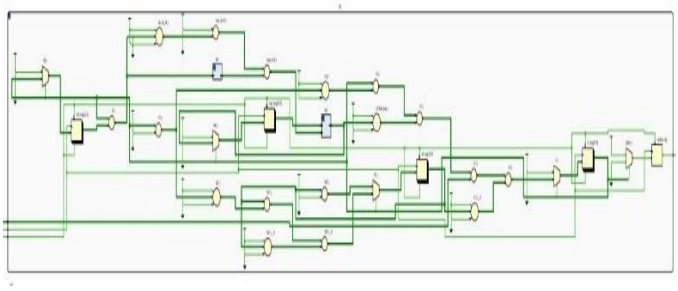

Fig_2: RTL view of AdEx neuron

RTL schematic obtained from Vivado for the proposed digital model of the AdEx neuron is given in Fig. 2. The resource utilization for the model is presented in Table I wherein the requirement for the implementation of exponential function is explicitly shown to compare with the results from [1] and [2]. It can be observed that the requirement of hardware blocks is much less that those reported in [2] while the accuracy is much better than [1].

III. RESULTS FROM THE DIGITAL ADEX NEURON MODEL

In order to validate the spiking characteristics, regular spikes generated by the digital model has been compared with those generated using the original AdEx model in MATLAB and the same are presented in Fig. 3. In addition, different spike patterns such as bursting and regular with spike frequency adaptation have also been generated using the digital model by tuning the parameters such as v_t and τ_ω and are presented in Fig. 4 and 5 respectively.

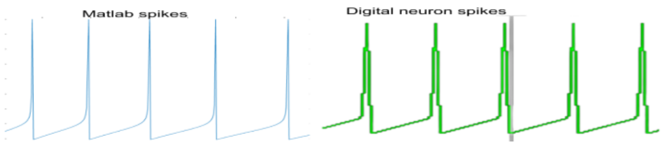

Fig 3: A comparison of spikes generated by the digital model with original AdEx model from MATLAB

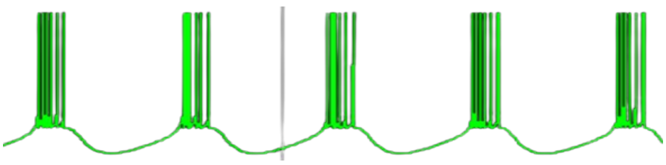

Fig 4: Bursting spiking pattern of AdEx neuron

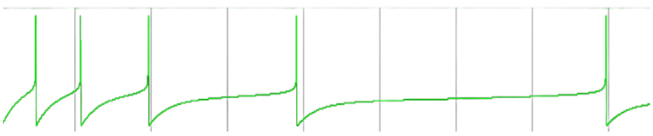

Fig 5: Adaptive spiking pattern of AdEx neuron

Further, ECG signal has been encoded using the proposed AdEx digital model and the result is given in Fig. 6 where the blue curve represents the ECG and the green spikes the encoded sequence. Three different cases of ECG signal have been encoded and it can be observed that the proposed digital neuron model follows the input ECG signal by accurately mapping the amplitude information in terms of temporal coding.

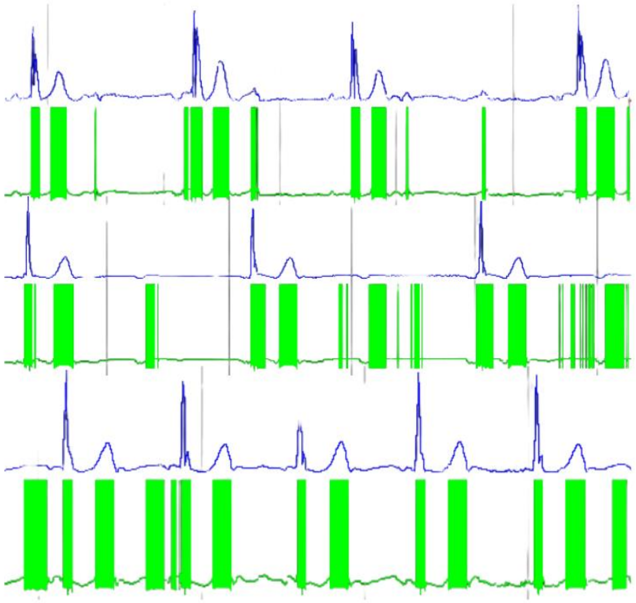

Fig 6: Temporal encoding of ECG by the AdEx model

TABLE I

Hardware utilization report of the Exponential block within the AdEx neuron and the AdEx Neuron as a whole

Name	Slice LUTs	Slice Registers	DSPs
Encoder	241	107	6
Exp. block	105	0	6

IV. ECG ALOMALY DETECTION AS AN APPLICATION

Characteristics of the ECG can be extracted from the temporal encoded spikes using a digital feature extraction block and classify the particular case of arrhythmia by feeding the extracted features to a Spiking Neural Network.

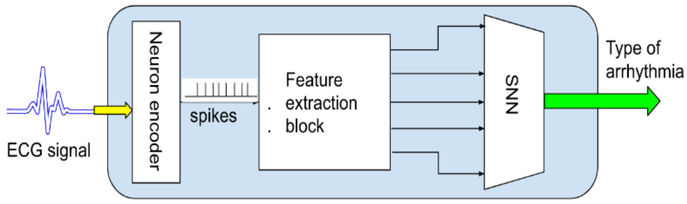

Fig 8: Block diagram of anomaly detection system

For future development we can incorporate adaptive threshold variation based on baseline wand of ECG for optimum encoding.

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