Neurons Don't Just Integrate: An alternate approach for music perception using Spiking Neural Networks

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***Abstract*—Detailed model for neural behaviour have existed for over half a century. With the advent of Moore's law, fabricable memristor devices and extensive study of neural behaviour, it is now possible to design chips that try to immitate the brain. However, to reduce the computational complexity, researchers have developed simplistic models to capture the behaviour of neurons into simple circuits. Models like LIF, AEF etc predominantly model the neuron as an integrator. In this paper, we present a class of properties that the integrators fail to exhibit but biological plausible and detailed models like Hodgkin-Huxley possess. We then use a Resonate and Fire (RF) model of the neuron, developed by Izhikevich et. al. [2001], which exhbits these properties, to compare its performance with a traditional Integrate and Fire model. We also demonstrate that certain biological phenomenon, involving music, possibly occur because of these traits of a neuron.**

I. Introduction

One of the most prominent neuron models that is being used in the state-of-art neuromorphic chips is the Leaky Integrate and Fire (LIF) model. Its computational simplicity and similarity to the more detailed and realistic models (Hodgkin and Huxley 1952, Morris and Lecar 1981) make it ideal for use in both the hardware as well as the software simulation domains. However, several properties of neurons, like the post inhibitory spiking and subthreshold oscillations are not exhibited by LIF. This deprives the current systems of computational capabilities that natural neural systems possess. The impact of these is visible when we want the neuromorphic systems to resonate or synchronize because these are direct consequences of the oscillations present in neurons. In [1], the author states that *The brain does not "solve" problems of missing fundamentals, it does not "compute" keys of melodic sequences, and it does not infer meters of rhythmic input. Rather, it resonates to music*

We discuss some of these properties of a biological neuron next.

A. Post Inhibitory Spiking

When a neuron is presented with a inhibitory pulse for a short duration, it rebounds after the pulse is removed and issues a spike. This phenomenon is observed in a large number of biological systems, for example the mesencephalic V neuron of the rat's brainstem [2] as well as the Hodgkin Huxley's (HH) model for the neuron. This is also known as anodal break excitation, rebound spike or more commonly as a postinhibitory spike. Figure 1a and 1b depict the response of the HH model and the Izhikevich model respectively when the aforementioned stimulus is presented. The dynamics of the Na^+ and K^+ channels are similar in both the cases, leading to a spike being issued in case of an inhibitory stimulus as well.

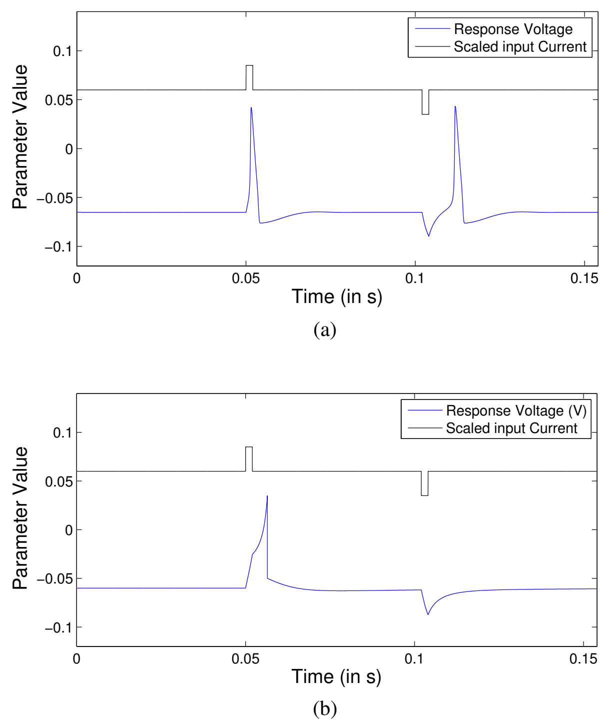

Fig. 1. Response of Hodgkin-Huxley's neuron model (a) and the Izhikevich's neuron model (b) to excitatory and inhibitory pulses of the same magnitude

B. Subthreshold Oscillations

While most models that are being used currently use integration to represent the neural dynamics, subthreshold oscillations are seen in neurons, which can lead to interesting behaviors such as resonance and synchronization, cannot be modelled by the integration process. In Figure 2, we show how such resonace can lead to constructive or destructive interference when multiple stimuli are presented to a neuron. When consecutive stimuli are presented in phase, the HH neuron spikes, whereas when they are presented out of phase, the subthreshold oscillations fade. Integrator models on the

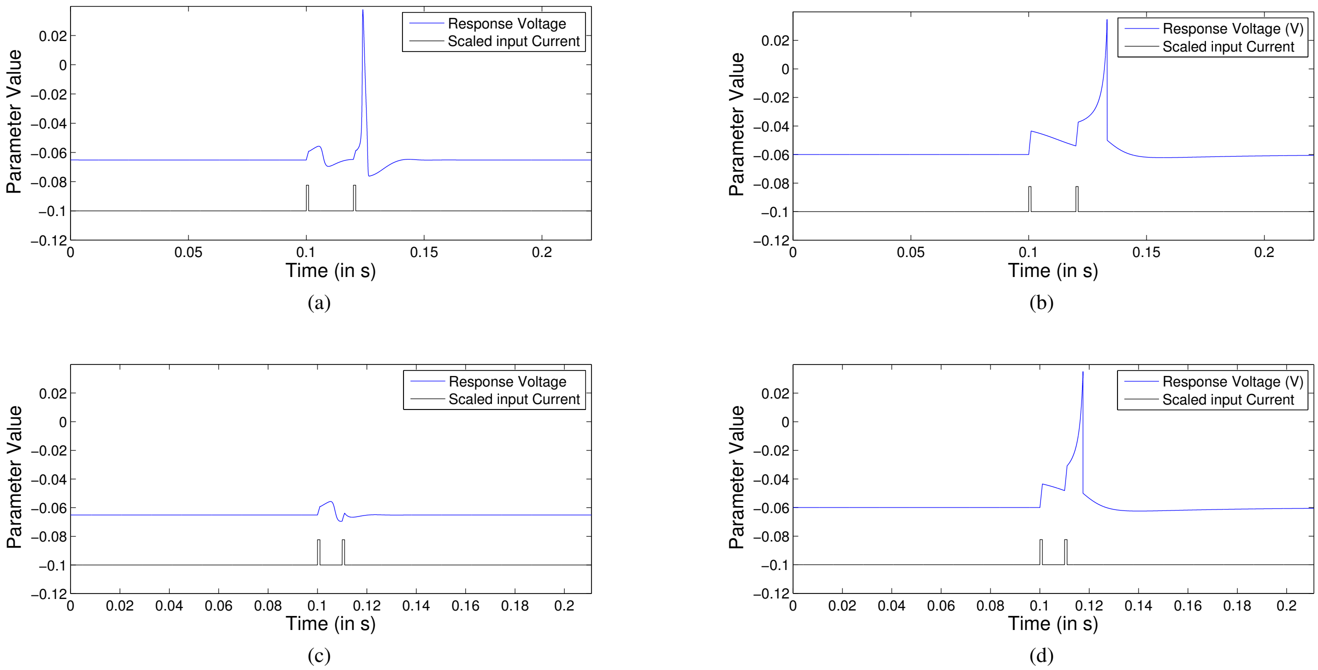

Fig. 2. Demonstration of subthreshold oscillations and interference in neurons which Integrate and Fire models fail to capture. Figures (a) and (b) show the response of HH and Izhikevich neurons to stimuli seperated by 20 ms, whereas Figures (c) and (d) capture the deviation in behavior when stimuli are placed closely together, at a gap of 10 ms

other hand tend to spike more aggressively if consecutive spikes are placed close together in time.

II. Resonate-and-fire neurons

Biological neurons possess subthreshold oscillations. Any perturbation in the state of neuron from its resting state leads to damped oscillations in its membrane potential. This is also the reason behind post-inhibition spikes. A large enough amplitude of oscillations due to an inhibitory input may generate post-inhibition spiking in neurons. The models of neurons having this property are called as resonate-and-fire neurons. Hodkin-Huxley model exhibits characterisitics of a resonate-and-fire model but leaky integrate and fire or adaptive exponential integrate and fire models do not.

A. Characteristics

As we know, integrate-and-fire type of neurons respond better to higher input spike rates of excitatory inputs. In other words, the output spike rate of integrate and fire neurons increases monotonically with increase in rate of excitatory spikes at its inputs. On the contrary, resonate-and-fire neurons are selective to the inter-spike interval of incoming doublets, triplets or bursts of spikes. The oscillations in its membrane potential give rise to oscillations in probability of the neuron spiking with time for a given input. On one hand, an input spike arriving during the trough of its internal oscillations may lead to removal of a spike which otherwise would have been issued. On the other hand, certain inhibitory inputs may give rise to a spike which otherwise would not have been issued.

Resonate-and-fire neurons have following two properties, which are important for music perception:

1) Entrainment: If a resonator neuron is excited with stimuli with a certain temporal structure, then its internal dynamics synchronize with external stimuli. This entrainment of intrinsic characteristics of a neuron may provide a basis for exlaining perception of a rhythm and synchronization with it.

2) Conincidence detection: The resonate-and-fire neurons are selective to inter-spike intervals of the input spikes. Probability of issuing a spike doesn't increase with decresing inter-spike interval. This property makes them a good candidate for coincidence detection applications. It is demostrated in Figure 3.

B. Model

Hodgkin-Huxley model is very computation intensive. Hence, simpler, computation efficient model of resonate-and-fire neuron proposed in [3] was used for simulations. Dynamics of the neuron are given by following coupled equations:

$$\dot{x} = bx - wy$$
$$\dot{y} = wx + by$$

Here, x is a current-like variable. It models the synaptic current dynamics. y is a voltage-like variable. b is he rate of attaraction to the rest state w is the frequency of oscillations The neuron is said to have spiked when y crosses a certain threshold, say $y_{th} = 1$. Above linear equations along with a non-linear reset at a spike given by

$$x \rightarrow x_0$$
$$y \rightarrow y_0$$

completely describe dynamics of the neuron model used.

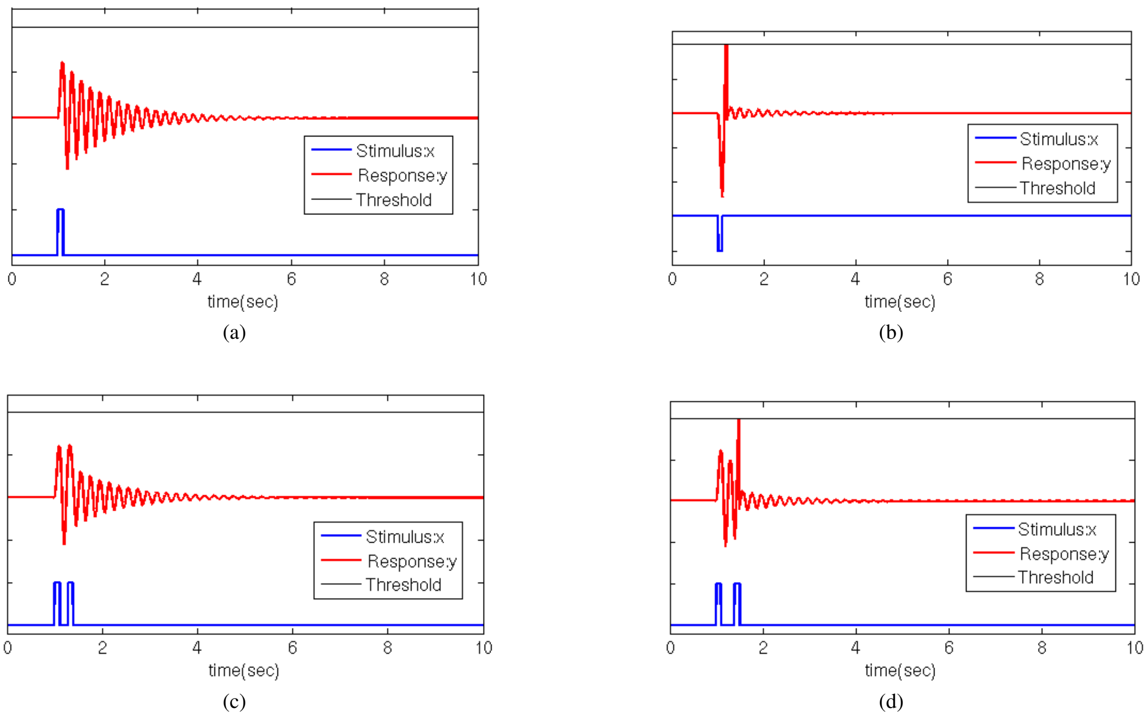

Fig. 3. Demonstration of selectivity of resonate-and-fire neurons to inter-spike interval: (a) Subthreshold oscillations (b) Post-inhibition spike (c) No spike elicited for small inter-spike inteval due to out-of-phase arrival (d) spike elicited for larger interspike interval due to in-phase arrival

III. Experimental Setup

We chose to test the RF model against the LIF for beat detection in an accented musical piece[1]. This piece makes beat detection easy and provides a benchmark that we can use to analyze the performance of neurons of different types and their response to musical inputs. As we wanted to test the performance of individual neurons, we set the resonance frequency (w), decay constant (b) and the spike threshold y_{th} of the RF model to a fixed value and fed the sound waveform to the neuron after appropriate scaling. The spiking pattern of the neuron, as shown in Figure 4 is extremely well-behaved. This is, however, due to the accented nature of the music piece. On unaccented pieces, similar behaviour was seen but in small localities, lasting upto a few seconds. The neuron could not remain synchronized to the entire piece.

An explaination to this could be that a musical piece is uniform in one phase, but the phase keeps changing from time to time. In each of these phases, there is a set of dominant frequencies which can be observed to track beats. We back this claim by observations of spiking behaviour that were made on changing the resonant frequency. As we changed the resonant frequency, synchronized spikes were seen over different patches.

A. Results

Figure 4 depicts the results obtained from the previous experiment. One can observe that there is a clear and constant phase shift in the strokes produced by a human subject and the spikes produced by the neuron. This is probably because of the delay associated with the motor control and decision making in the brain. The stroke timings obtained from the subject have been readjusted by deducting the gap between the first stroke and the first spike. Readjusted strokes appear to be synchronized to the neural output.

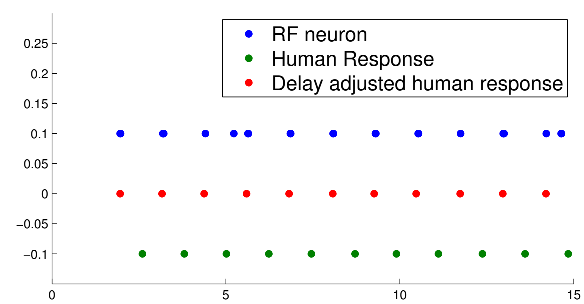

Fig. 4. Experimetal results

IV. Conventional Methodology

Conventionally, acoustic perception is modelled using gammatone filterbanks [4] that model the basilar membrane. We tried the same approach, splitting the available frequency range (100 Hz - 5 kHz, resulting from a sampling frequency of 10 kHz) into 10 bands and feeding the filtered sound waves to different LIF neurons after half-wave rectification and compression by a $1/3$ power law.

$$I_i = k[x_i^+]^{1/3}$$

[1] Notes are being played on each of the beat counts

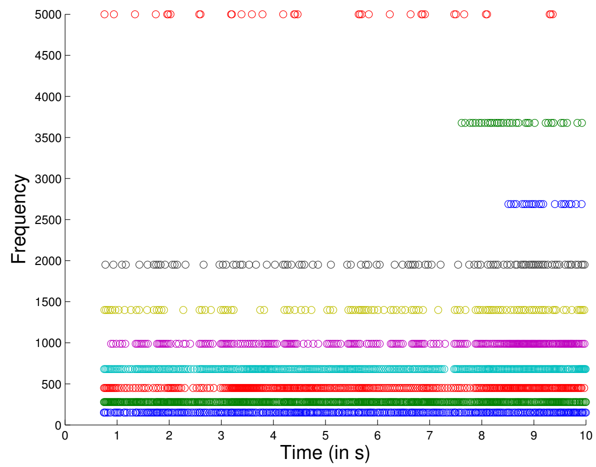

Fig. 5. Spectro-temporal spike raster plot for analysis of a music piece using Integrate-and-Fire model of the neuron

Similar transformations have been used elsewhere for audio source localization using Spiking Neural Networks (SNN) and gammatone filterbanks, as in [5]. The neurons are fed this current using synapses with constant weights. The spike patterns as observed in Figure IV can possibly be used to extract rhythms but it appears that we need to implement complex networks to obtain synchronization in these networks because of multiple reasons.

- Lack of inherent resonance makes neurons spike at very high frequency for low frequency inputs and at rather low frequencies for High frequency inputs, as can be inferred from Figure IV
- It appears that burst synchronization can be used to synchronize the higly active neurons but it requires a complex network as compared to what we propose while concluding
- Gammatone filterbanks further increase the complexity of the network

V. Conclusion

In this paper, we explore a different model for a neuron that exhibits some of the properties that the integrator neurons do not. Moreover, this model is computationaly as inexpensive as the LIF model. We also verified its performance for tasks involving synchronization which appear to be natural to humans. We tried to perform beat detection using the resonate-and-fire model and noted very similar behaviour to that of a human subject for a rudimentary case. We have demonstrated certain characteristics of this model which might be helpfu in explaining music perception and synchrony. In the future, we would like to explore the behaviour of a network of such neurons with different resonant frequencies, connected via plastic synapses, when stimulated with music.

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