

## **Brian Simulation Using the Leaky Integrate and Fire Neuron for Edge Orientation Detection**

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### **ABSTRACT**

We present in this paper a new approach along with the first results for the edge detection of a moving object as a future target due to its importance in the field of robotics and prosthesis. The approach is based on using a simulator with a mathematical model that resembles the biological behavior of a neuron and build on that for future continuation of the work in order to move from software into a hardware and real time application parts.

### **KEYWORDS**

**Brian simulator, Neuron model, Leaky Integrate and Fire Neuron (LIF).**

### **1 INTRODUCTION**

Nowadays with the development in technology and fields of science, tactile sensing became an important leader in various applications such as robotics, car industries, electro textiles and medical prosthesis. In robotics, the tactile information, being the fundamental agent, is needed during tasks like manipulation and exploration [1]. Thus, the interactive way of robots with the real world objects is an important issue - as such interactions depend on how heavy or light and smooth or hard the objects.

With the advancement in technology and science over the years, the tactile sensing in artificial devices has improved and wide spread in addition to the generation and production of many force/pressure

sensors and sensing arrays, using different materials and transduction methods [2]. Moreover, the importance of edge detection in different fields pushed good number of research groups to make use of the latter advancements and tried different ways and combinations in order to detect the orientation of moving edges [3].

Comparable to the importance of electronic circuit simulators in mimicking biological neurons and their behaviors, mathematical models are being built, developed and implemented in different programming softwares [4]. This approach aims to give a push to scientific research for a better understanding of different phenomena that attract scientists to explore and understand from one side and to test its feasibility to be implemented on circuit simulators first and on hardware as a last step on the other side.

In this paper, we present the starting phase of the work that aims for detecting the edge orientation of a sliding object on a complete patch of a robot skin. The paper is divided into the following sections: Section 2 deals with the methodology and work flow. Section 3 talks about the Brian simulator and its features. Section 4 describes the model being considered. Section 5 includes the discussion of the results shown in section 4.

## 2 EDGE ORIENTATION DETECTION: METHODOLOGY

The fundamental goal behind this work is to detect the orientation for a sliding object over the skin of an artificial device such as robots. To achieve this, the presence of a simulator at first helps to test the reliability of the neural network for the sake of detecting the orientation based on their response.

To do this, we use through the simulator a group of neurons with defined indexes and spatial position to record their response over time by means of spike trains. The overlapping of the neurons response over time will highlight the flow of the object across the patch of skin over time and therefore the detection of the orientation of the latter.

## 3 BRIAN SIMULATOR FOR SPIKING NEURONS

The mathematical model, described in the coming section, is built in Brian using Python object oriented programming language. The simulator is aimed to develop models based on networks of spiking neurons for a wide range of applications. Users specify neuron models by stating their own differential equations in standard mathematical form as strings, create groups of neurons and connect them via synapses. This approach differs greatly from many neural simulators in which users select from a predefined set of neuron models (refer to [5]).

## 4 MATHEMATICAL MODEL

Our model extends from [6]. We modified the model in a way to preserve the activity of the Leaky Integrate and Fire Neuron (LIF) and eliminating the adaptation part. Thus, the membrane of the LIF is modeled by a differential equation shown in Equ.1, that mimics its real behavior  $v_m$ ,

with a set of state variables such as the input current to the neuron  $I$ , reset potential  $E_L$ , leak conductance  $g_L$ , membrane capacitance  $C$ , slope factor  $\Delta T$ , spike threshold  $V_T$ .

$$\frac{dv_m}{dt} = (g_L * \Delta T * \exp(\frac{v_m - V_T}{\Delta T}) + g_L * (E_L - v_m) + I) / C \quad (1)$$

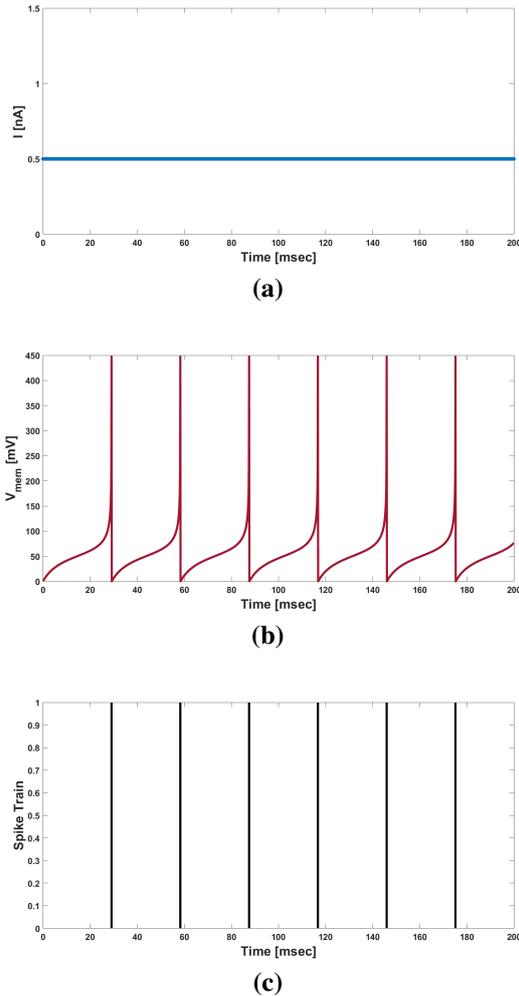
Specifying the differential equation with the set of state variables and the numerical integration method makes the contents of a single or group of neurons ready to be initiated. With the capabilities of the simulator for transient analysis, the latter makes it possible to show the input current over the time duration similar also for the membrane potential. Moreover, having the ability to save the spiking instants, spike trains, associated to each neuron included within the group, can be represented versus the instant the spike is generated.

## 5 RESULTS

As the model includes a group of neurons, the following results show the response of one neuron as at first and a group of neurons after being fed by constant input, their outputs and the spike train corresponding over time.

Starting with a single neuron, Fig.1 shows three different transient plots. Fig.1a shows a constant input current fed to the neuron along with its response by means of its membrane potential (see Fig.1b). The latter is considered the profile of the LIF neuron. Fig.1b comes as result of Fig.1a where each spike generated is associated with a digital pulse as shown.

Fig.2a shows a variable input current fed to the single neuron along with its response by means of its membrane potential (see Fig.2b) and spike trains associated in Fig.2c.

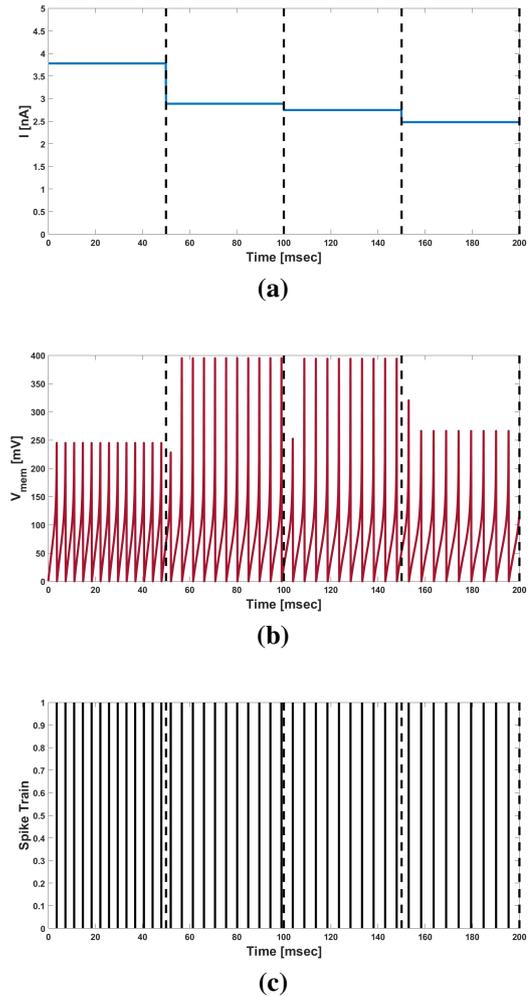


**Figure 1.** (a) Input current to the neuron versus time.(b) Membrane potential as a response of the integrated input current over time.(c) Spike train displaying the different instants of each spike.

In Fig.3, a group of three neurons is considered (i.e. 3 neurons); where different input currents are fed to. Fig.3a shows their responses by means of their membrane potentials. In Fig.3b, a raster plot is displayed. Fig.3c includes the transfer function of the model having the firing rate (as output) as function of the input current (as input).

## 6 DISCUSSION

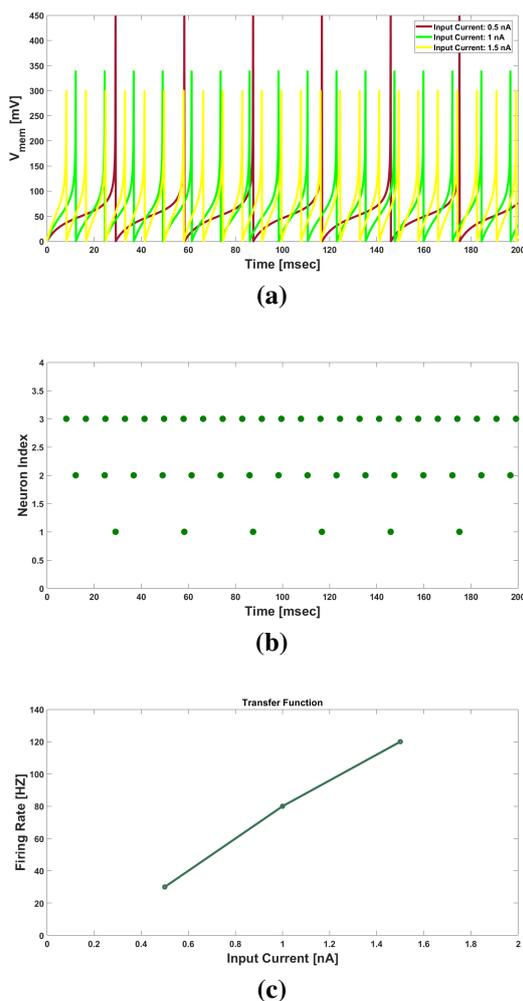
Concerning Fig.1, the neuron starts charging as the input current is integrated into its membrane until the reset voltage



**Figure 2.** (a) Variable input current to the neuron versus time.(b) Membrane potential as a response of the input current over time.(c) Spike train displaying the different instants of each spike.

is crossed and it sharply discharges. It continues with this behavior all over the duration of time (i.e. 200ms). In addition, this behavior proves the modifications done to the model in such a way that the normal behavior of the LIF neuron is achieved and resembles that found in literature [7] without adaptation.

In Fig.2, the duration is divided into four intervals, 50ms per each. The response of the neuron shows that the more current is integrated, more spikes are generated over



**Figure 3.** (a) Membrane potential of three neurons as a response of the input integrated current over time.(b) Raster plot.(c) The transfer function of the model.

the time interval considered.

To show the response of different neurons as a matter of the input current, Fig.3 serves for this. Three neurons are considered and fed by three different input values(0.5 nA,1 nA,1.5 nA) are set. The response for this of neurons is compatible with that in Fig.2. Fig.3b shows the raster plot for the three neurons that highlights the instant a spike is generated and the index of its corresponding neuron. The importance of Fig.3c is to emphasize that the increase in the firing rate of the neuron comes out as

a result of increasing the input current. That is why the firing rate increases proportionally with the increase in the input current.

## 7 CONCLUSION

In this work, we stated a general description of a mathematical model under study. The purpose behind such model is included and clarified in a way to get an insight into its functionality as a part of current research issues. In addition, we presented and explained some results of such model as a cornerstone for our specific aim in detecting the orientation of a sliding object over a robot patch of skin.

## 8 REFERENCES

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