Experiments with Izhikevich Model of Spiking Neuron

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Abstract

Neurons are the fundamental processing units in the brain and central nervous system. When a neuron receives a stimulus, it produces action potentials (electrical impulses) that are propagated along its axon. The neuron gets excited and they fire a voltage spike when they get stimulated. Eugene M. Izhikevich proposes a computer simulation using computationally simple model which produce the spiking patterns exhibited by a biological neuron. This paper studies the change of the spiking pattern by varying the input and a simple network made with two such neurons.

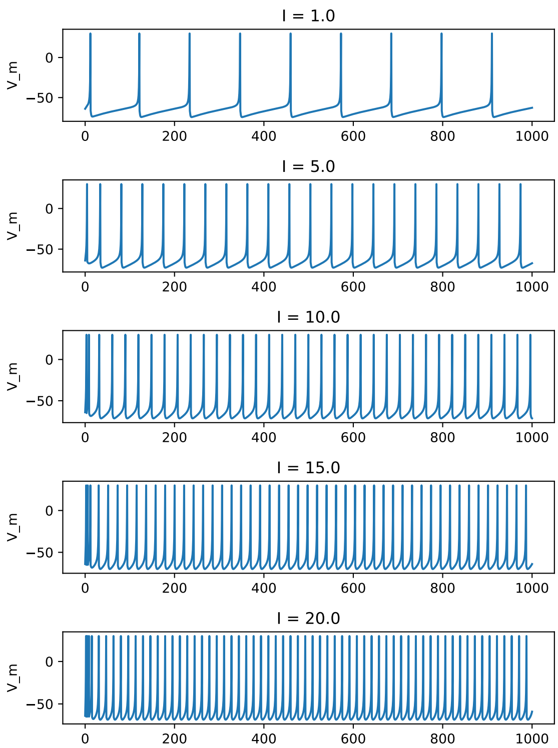
1 Effect of varying input (I) on Spiking Voltage (V)

1.1 Problem Statement

Izhikevich (2003, 2004) proposed a computationally simple model to simulate the spiking patterns in a biological brain. Unlike the Hodgkin-Huxley model, the Izhikevich model does not account for the biophysics of neurons. It uses mathematical equations to compute a wide range of spiking patterns for cortical neurons. The output is incredibly realistic and biologically plausible.

For this experiment, we first create a simple neuron model based on the *Regular Spiking Neuron (Izhikevich 2004).* We then try to study the changes in the spiking voltage by driving the neuron with varying input signals. Input (I) ranges from 0.0 to 20.0 in increments of 0.5. Each Input for the neuron is driven for 1000 timesteps. When the output voltage is greater than the threshold voltage of 30mV, we consider that signal to be a spike. We then calculate the Mean Spiking Rate (R) for the last 800 steps. Spiking rate is calculate by calculating the number of spikes in the last 800 steps divided by 800.

1.2 Results



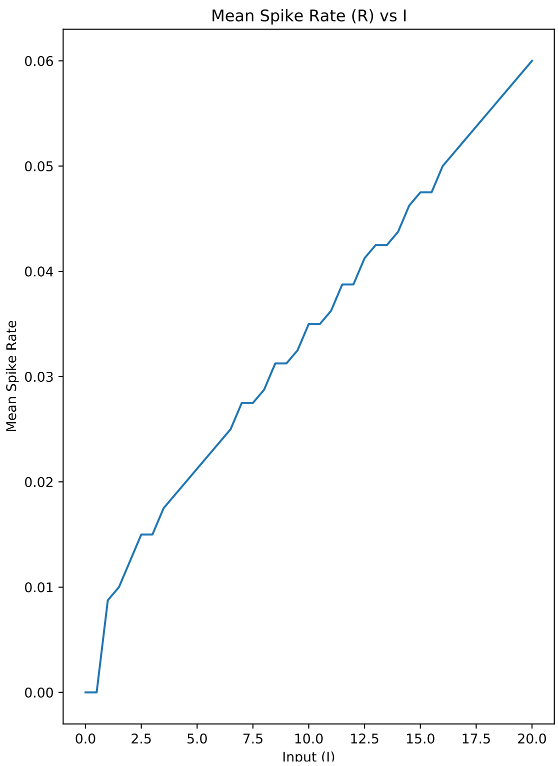


Figure 1: (L)*Plot of Simulation of a single neuron for 1000 steps by driving it with different inputs.*

Figure 2: (R)*Plot of mean firing rate as a function of input I for a single neuron. The firing rate is calculated by averaging over the last 800 time steps of a 1,000 time step simulation.*

1.3 Discussion

From Figure 1. it can be observed that there is positive correlation between input I and the Spiking Rate. With the increase in Input to the neuron, the Spiking Rate increases accordingly. This happens by having more spikes or actuation in a particular time period

From Figure 2. it can be observed that the mean spiking rate increases with the increase in the input value. This is expected as the number of spikes and spiking rate are directly related. It can also be observed that the spiking rate and the input I is linearly dependent. This is supported by the equation for dv/dt (Izhikevich 2003).

1.4 Conclusion

The simulation of the neuron with varying input values almost mimic the biological neuron. It can also be observed that the rate of firing can be controlled by varying the input. In practical applications, this neuron could be used as a computational unit in a neural network. The 30mv threshold acts as the activation function which controls the firing of neurons.

2 Simple network with Izhikevich neurons

2.1 Problem Statement

For this experiment, we create a simple neural network model using two neurons (A and B) as shown in Figure 3. The output signal (y_A) factored using weight (w_{BA}) which acts as the synaptic weight. This is then combined with the input signal (I_B) and the resultant serves as the input ($I_B(t)$) for the neuron

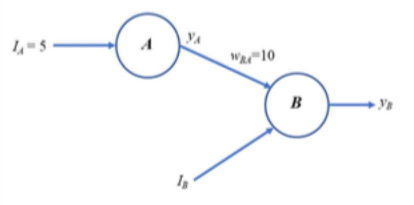
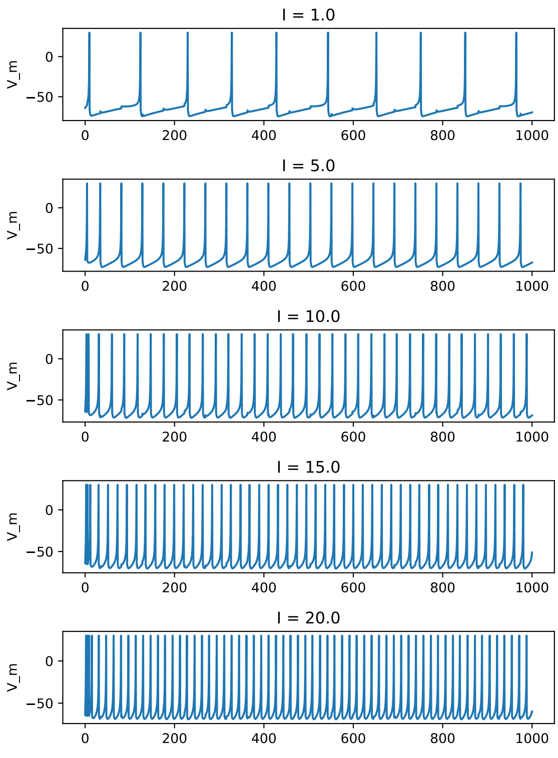


Figure 3: *Two-neuron system*

This neural network is driven with varying input (I_B) ranging from 0 to 20 in 0.5 increments. The experiment is carried out for 1000 timesteps. Similar to experiment 1, we calculate Mean Spiking Rate.

2.2 Results



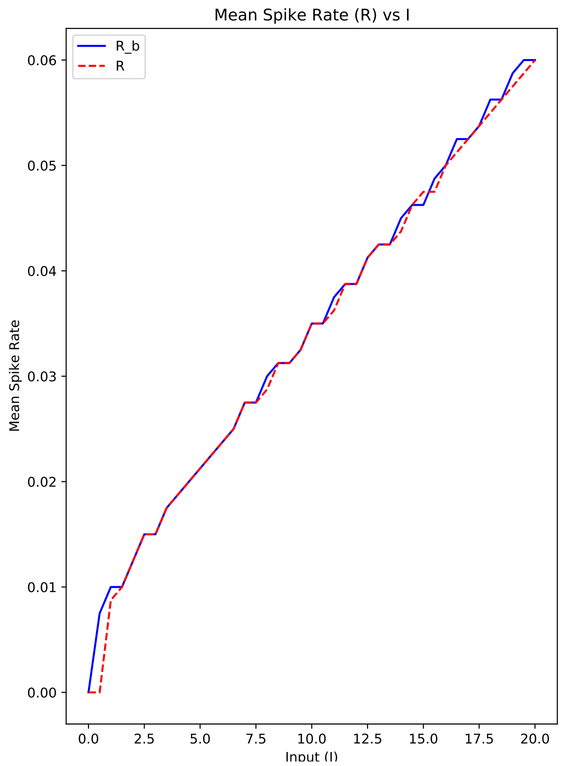


Figure 4: (L)*Plot of Simulation of a network of two neurons for 1000 steps by driving it with different inputs.*

Figure 5: (R)*Plot of mean firing rate as a function of input I for a network of two neurons. The firing rate is calculated by averaging over the last 800 time steps of a 1,000 time step simulation.*

2.3 Discussion

Similar to Experiment 1, the Number of spikes increases with the increase in I as shown in Figure 4. When comparing the case of single neuron (Figure 1) and Network of two neurons (Figure 4), both have similar nature. The difference can be observed when $I_B = 0$, in case of single neuron we observe 9 spikes while the neural network produced 10 spikes

From Figure 5. it can be observed that the mean spiking rate increases with the increase in the input value. Both the spiking rates R_B and R are linearly dependent on input I_B. And they almost overlap with each other.

2.4 Conclusion

By combining the neurons with weights, we can generate a neural network. The 30mv threshold acts as the activation function which controls the firing of neurons. We can observe that the spiking rate for a single neuron (R) and network of two neurons (R_B) almost overlap with each other. Thus the firing pattern of the initial neuron is conserved even after it travels through another neuron. This behavior is expected as the biological neurons uses the similar method to send signals to long distances. The intermediate neurons acts as amplifiers to conserve the signal. We can thus connect many such neurons in series to mimic the biological neuron. And the spike rate or the signal from the first neuron will be similar to the signal even in the last neuron. Thus the spike rate is conserved and the signal is communicated in a loss less manner.