In The Name Of God

HW01

Advanced Neuroscience

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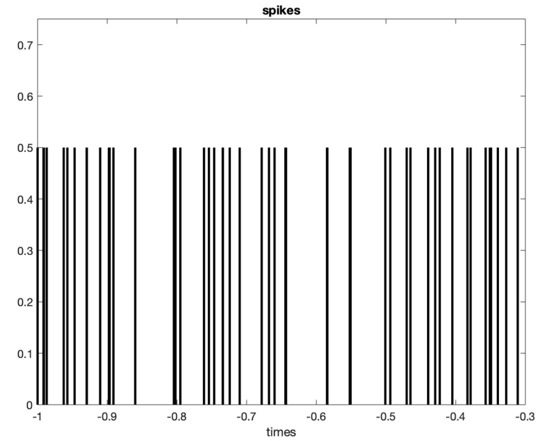
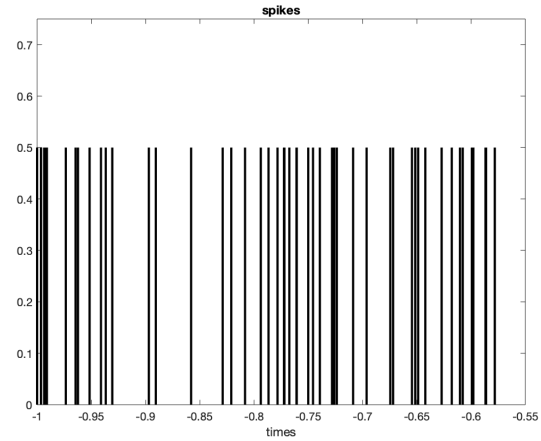
■ Integrate and Fire Neuron

□ part a

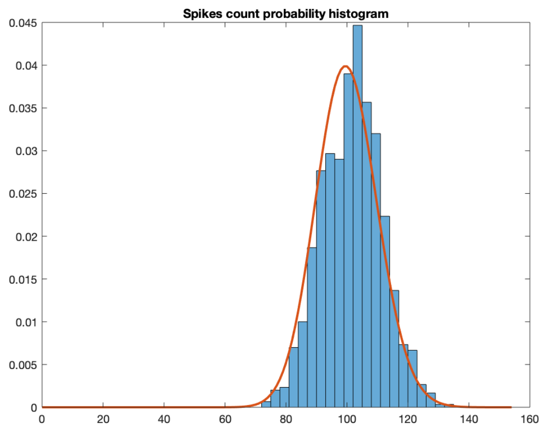


(a) Spikes train generated by Uniform

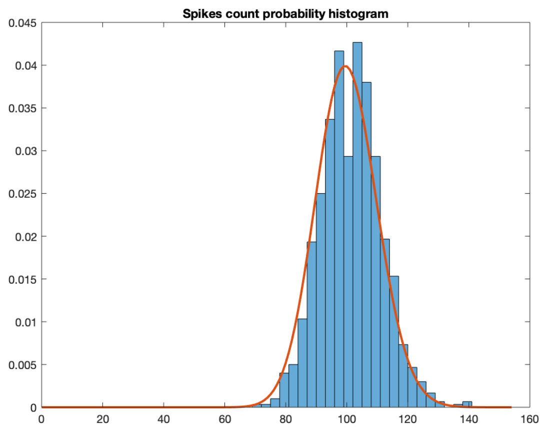


(b) Spikes train

□ part b



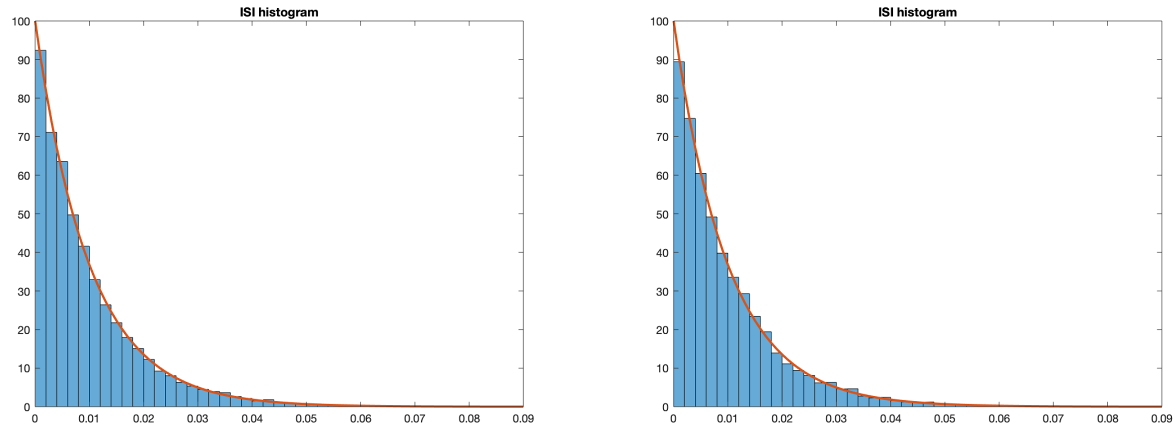
(a) Count probability histogram - Uniform



(b) Count probability histogram - Poisson

Figure 2: Count probability histogram

☐ part c



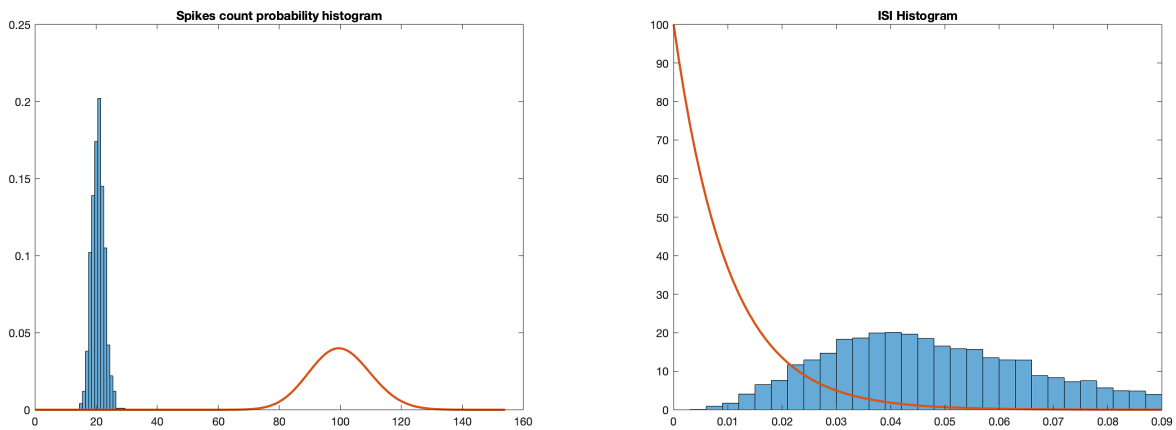
(a) ISI histogram - Uniform

(b) ISI histogram - Poisson

Figure 3: ISI histogram

The red lines that are fitted to the top Figures 2 and 3 are the theoretical probabilities.

☐ part c - renewal process



(a) Count probability histogram - Renewal

(b) ISI histogram - Renewal

Figure 4: Count probability and ISI histogram

Choosing each k_th spike is similar to downsampling the spike train by factor k. This is similar to integration over postsynaptic input. A postsynaptic neuron needs some spikes to fire a spike itself, so after getting a spike train as an input, it will integrate over the spikes and after k spikes it will make an action potential. If you look at the Figure 4, you can see that the histograms have gamma distribution.

☐ part d

A poisson process theoretically has a C_v equal to 1. C_v of the generated poisson spike train is 0.994 and C_v of the renewal process is 0.4535.

☐ part e

Let the intra spike interval (ISI) of poisson process be the sequence $X = (X_1, X_2, ...)$ and the ISIs of the renewal process be $T = (T_1, T_2, ...)$. It is known that:

$$T_k = \sum_{i=1}^{k} X_i$$

Note that X_is are i.i.d with exponential distributions. Then we have:

$$\begin{aligned} E[T_k] &= E[X_1 + X_2 + X_3 + ...] = \tfrac{k}{\lambda} \\ Var(T_k) &= Var(X_1 + X_2 + X_3 + ...) = \tfrac{k}{\lambda^2} \\ C_v &= \tfrac{std[T_k]}{E[T_k]} = \tfrac{1}{\sqrt{k}} \end{aligned}$$

☐ part f

As reported in the figure 3 of the Softky and Koch paper, the system is non-stationary. C_v of real data (Figure 3 Softly and Koch) at lower firing rates in V1 is between 0.4 and 1 and at high firing rates it is less than 0.4. So the variability of the real data is different than the variability of generated data.

☐ part g

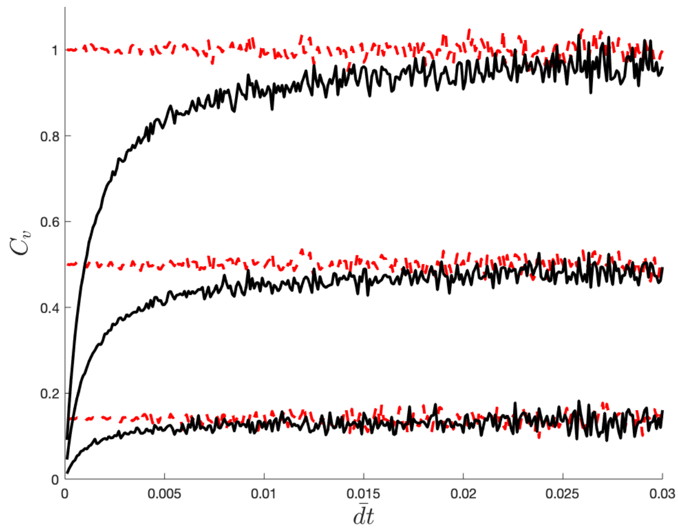


Figure 5: Reconstruction of the figure 6 of the paper

■ Leaky Integrate and Fire Neuron

□ part a

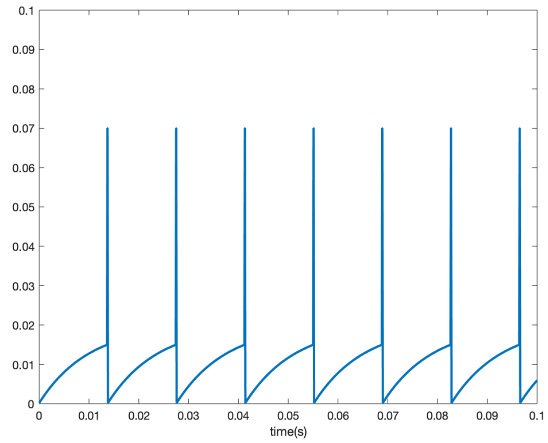
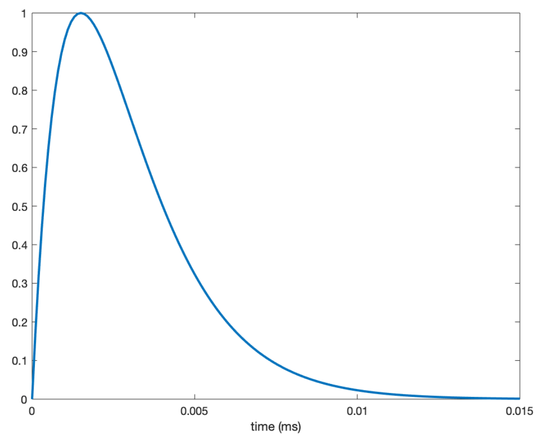


Figure 6: LIF Neuron Simulation, $\tau_m = 10ms$, RI =$20mV$, $dt = 0.0001$

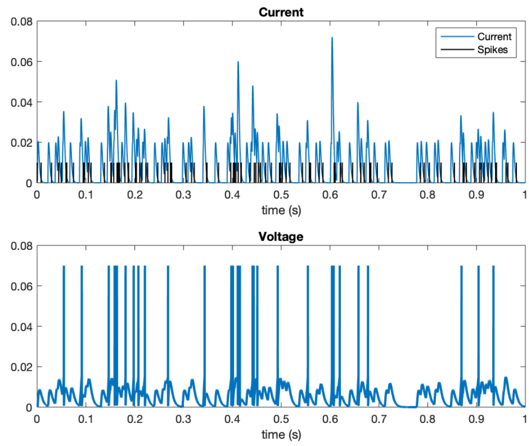
□ part b

$v(t) = RI(1 - e^{\frac{-t}{\tau_m}}) \rightarrow$ After passing the treshold we have $RI(1 - e^{\frac{-t}{\tau_m}}) = v_{th} \rightarrow 1 - \frac{v_{th}}{RI} = e^{\frac{-t}{\tau_m}} \rightarrow$ $t = -\tau_m \ln 1 - \frac{v_{th}}{RI} \rightarrow T = t + \delta t_r \rightarrow \frac{1}{T} = \frac{1}{-\tau_m \ln(1 - \frac{v_{th}}{RI}) + \delta t_r}$.

□ part c

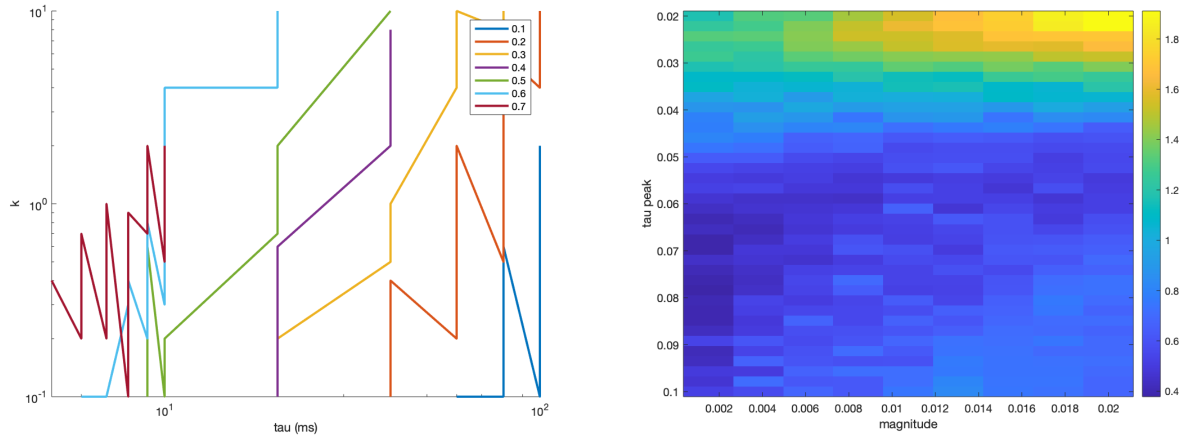


(a) Kernel in the Time Domain



(b) Current and Voltage of the Neuron

Figure 7: LIF Neuron Simulation - v_{th} = 15mV, v_r = 0, v_{sp} = 70mV, RI = 20m, tau_m = 10ms, t_{peak} = 1.5ms



(a) C_v vs τ and k

(b) C_v vs kernel magnitude and width

Figure 8: Figure 8 of the paper and the effect of Kernel properties on the C_v

In order to reconstruct the Figure [8] of the paper, the output mean firing rate should stays around 200Hz. A set of number of Fr_s are found so that the mean firing rate stays at 200Hz for each τ_m. Then for every τ_m I simulate the model for 30 seconds and then calculate the C_v.

As N_{th} $(N_{th} iseqaltokinmyFigures)$ becomes smaller, C_v becomes larger. Effect of width and magnitude of the EPSCs on C_v is analyzed in the Figure 8 - b. It shows that C_v slightly increases as the magnitude of EPSCs gets bigger and it marginally gets bigger than 1. Also it shows that τ_{peak} doesn't have any affect on the C_v.

□ part d

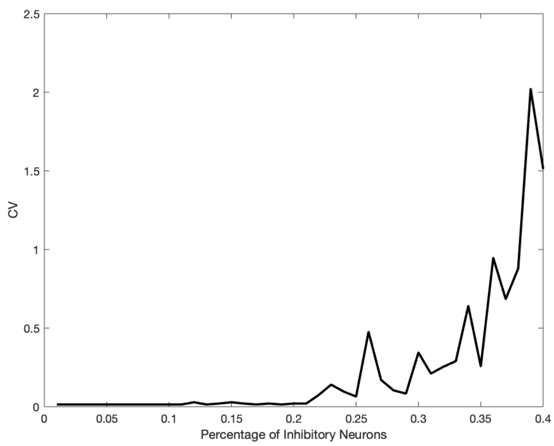


Figure 9: Effect of percentage of the inhibitory neurons on C_v

As you can see in the Figure 9, C_v rises as percentage of inhibitory neuron increases. It is noteworthy to mention that the output neuron may not fire if the percentage of inhibitory neurons is greater than 50-60%, so I applied a limit on the x-axis to show only 0-40%.

☐ part e

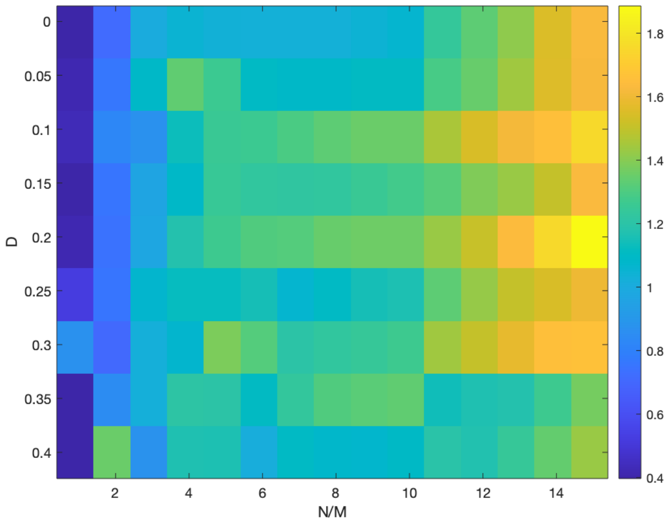


Figure 10: Effect of inhibitory neurons on C_v

As can be seen in Figure 10, Increasing $\frac{N}{M}$ causes an increase in C_v and increasing the D causes a decrease in C_v. Larger window sizes will increase the probability of spiking significantly therefore firing becomes more probable and C_v decreases. When $\frac{N}{M}$ is too big, the probability of occurring an spike is so low, therefore the C_v decreases.

☐ part f

The results should be similar to the results in the Figure 10, because if the number of the inhibitory neurons be small, they won't have such a big effect on the C_v and if their number is so big, the post synaptic neurons wouldn't be able to fire an action potential.