Advance Neuroscience HW7

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Question 2

Theoretical Derivation:

$$dX(t) = Bdt + \sigma dW(t), \quad dW(t) \sim N(0, dt) \Rightarrow E[dX(t)] = Bdt + 0 = Bdt \Rightarrow \boldsymbol{E[X(t)] = Bt}$$

And

$$Var(dX(t)) = 0 + \sigma dt = \sigma dt \Rightarrow \boldsymbol{Var(X(t)) = \sigma t}$$

Finding $X(t)$ distribution:

$$X(t) = X(0) + \sum_{n=1}^{t/dt} Bdt + \sigma dW(n) = Bt + \sigma \sum_{n=1}^{t/dt} dW(n)$$

So,

$$\boldsymbol{X(t) \sim N(Bt, \sigma t)}$$

Figure 1 show the variance and mean of the decision variable versus time.

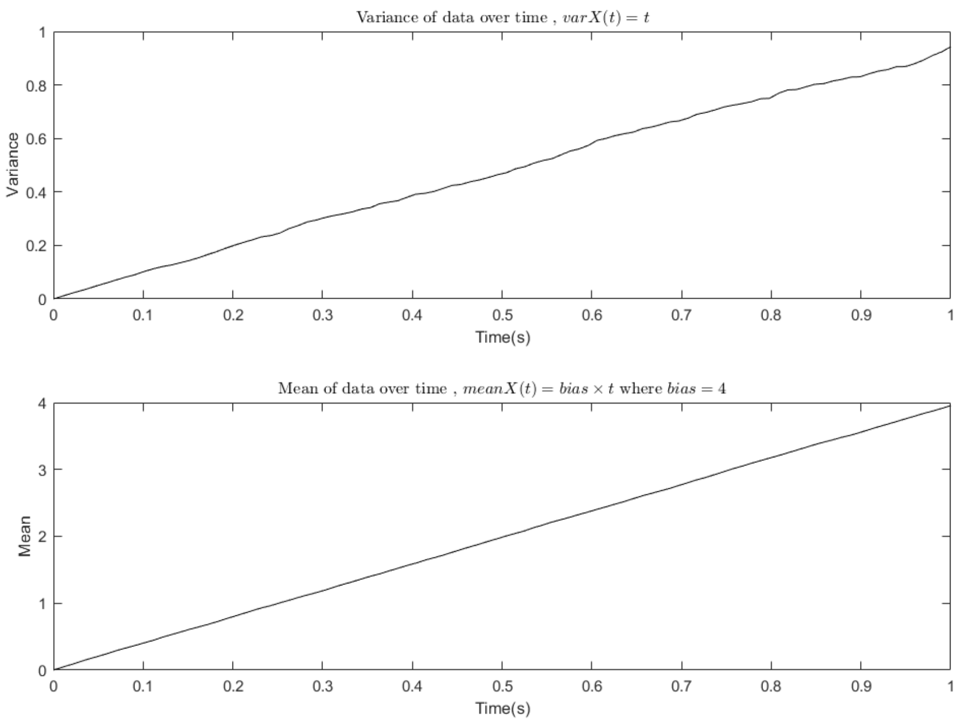

Figure 1: The simulated values for variance and mean of the data. It can be seen that it fits the theoretical derivations.

By taking $sign(X(t = end))$ as the final choice, we would have a Bernoulli distribution with parameter p as bottom:

$$p = P(X(t_0) > 0) = \int_0^\infty P_{X(t_0)}(t)dt = \int_0^\infty \frac{1}{\sqrt{2\pi(\sigma t_0)}} e^{\frac{-1}{2(\sigma t_0)}(t-Bt_0)^2} dt$$

and

$$choice \sim Bernoulli(p)$$

In this particular example from simulation $p \simeq 0.83$ and the theoretical value is $p \simeq 0.8413$. By simulating for different bias, we get figure 2.

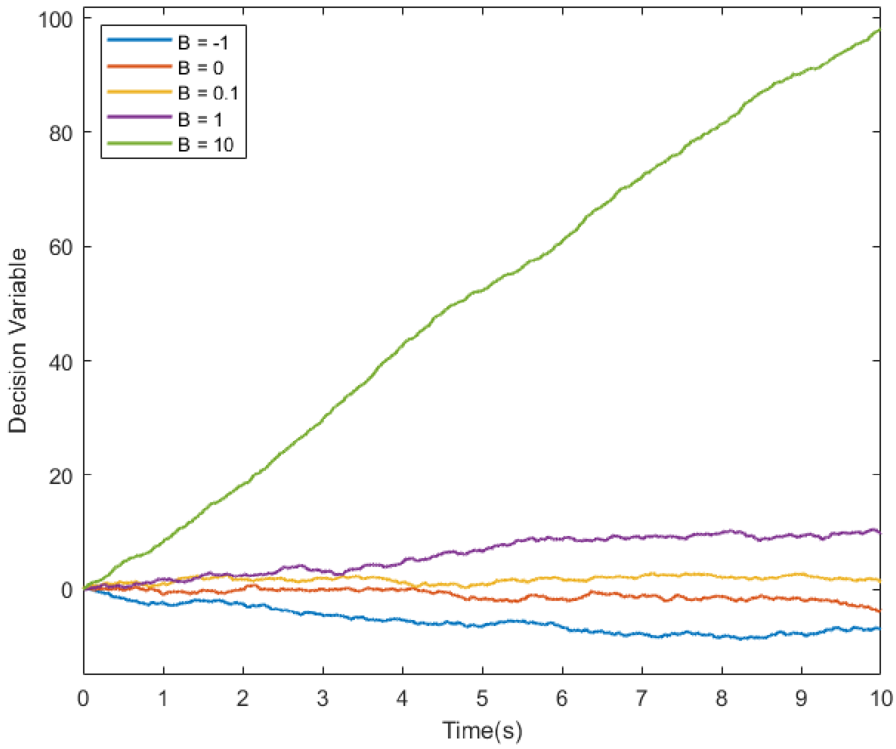

Figure 2: The bias values are shown in the legend.

Question 3

Using the theorerical equations that we derived before,

$$P_{Error} = 1 - P_{choice} = 1 - P(X(t) > 0) = P(X(t) < 0) = \int_{-\infty}^{0} \frac{1}{\sqrt{2\pi(\sigma t)}} e^{\frac{-1}{2(\sigma t)}(\tau - Bt)^2} d\tau$$

Figure 3 is the simulated error (black) alongside theoretical error (red).

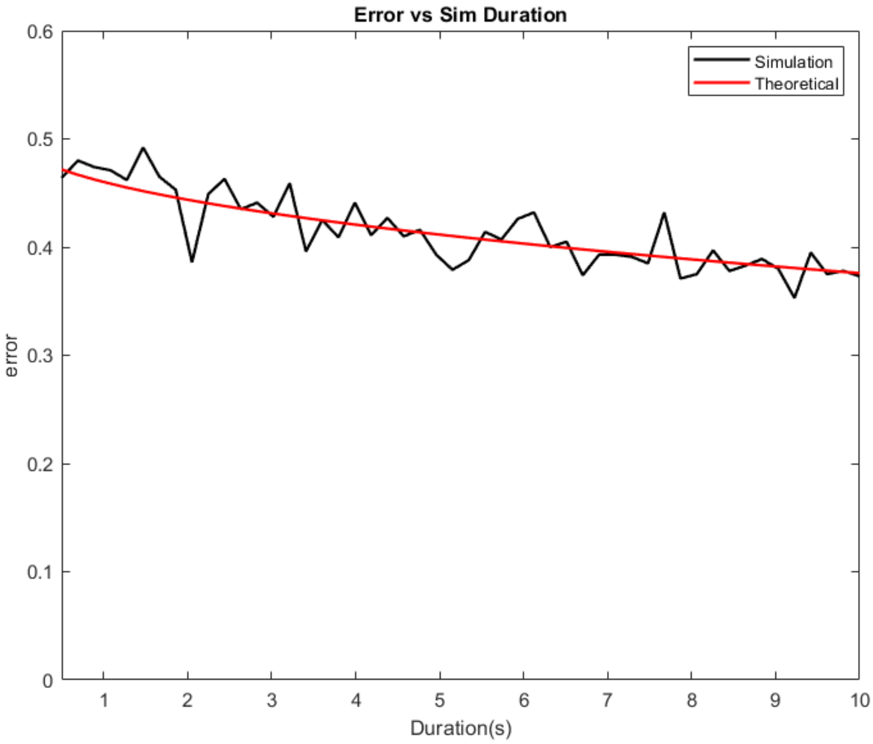

Figure 3: Error vs Duration

It can be observed that as the time goes on, the error decreases. That is because in more time, more evidence has been accumulated and we would be more confident.

Question 4

Figure 4 is the simulation alongside theoretical calculations for mean and std.

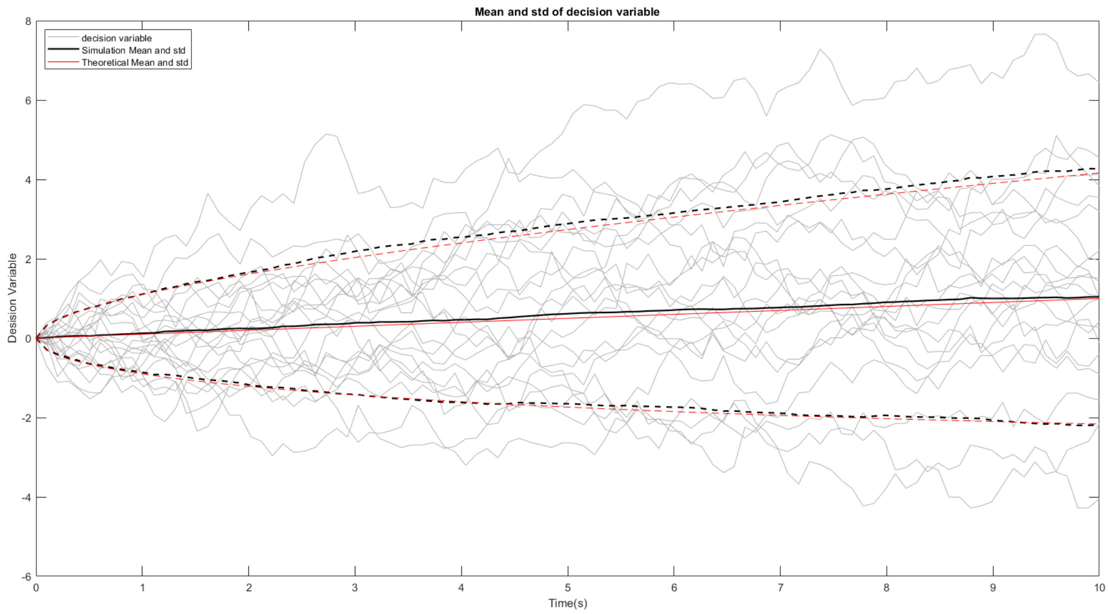

Figure 4

As can be seen from the figure, The decision variable for all trials almost rest within the $\mu \pm \sigma$. Theoretically 68.2% of the data is inside this interavl. Also, we have:

$$\mu = Bt, \qquad std = \sqrt{\sigma t}$$

Question 5

By changing the starting point from -6 to 6 for different time limits, we get figure 5

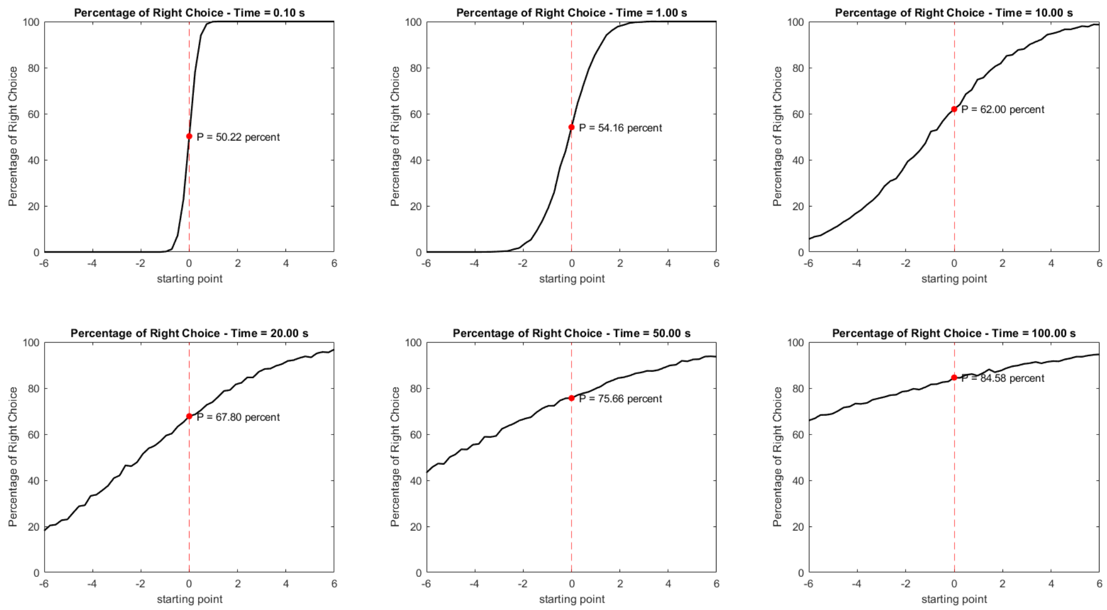

Figure 5: Effect of starting point on percentage of choosing right choice for different time limits

First let's discuss. First, the longer it takes for you to decide between the choices, the less you have confidence in your choice. For example if you decide between the choices in 1 seconds and in 50 seconds, you are probably more confident in 1 seconds. Also, when you are more far from 0, the probablity that you choose the right answer is more.
In figure 5 we can see both the things that discussed in the last paragraph.

Question 7

The distribution of RT values with the parameters,

$$\theta_+ = 5 \quad \theta_- = -5 \quad B = 0.1 \quad \sigma = 1 \quad x_0 = 0 \quad dt = 0.01$$

and for 10000 trials is as figure 6

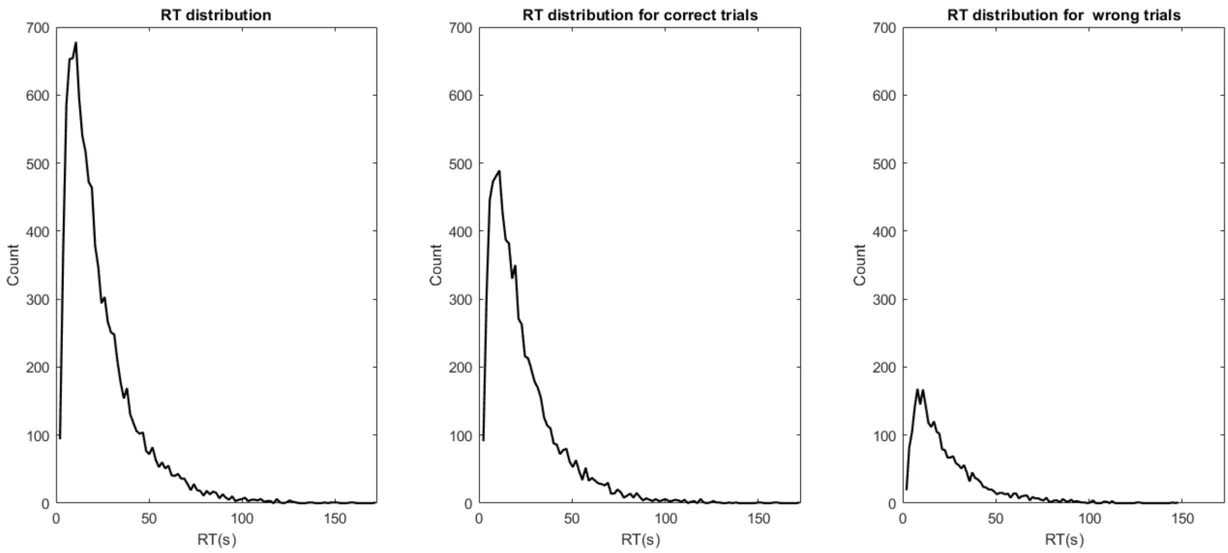

Figure 6: Histograms of RT values

If we normalize the counts of correct trials and wrong trials, we can see that they have the same distributions. As learned in the lecture, the distributions are "inverese Gaussian". (figure 7)

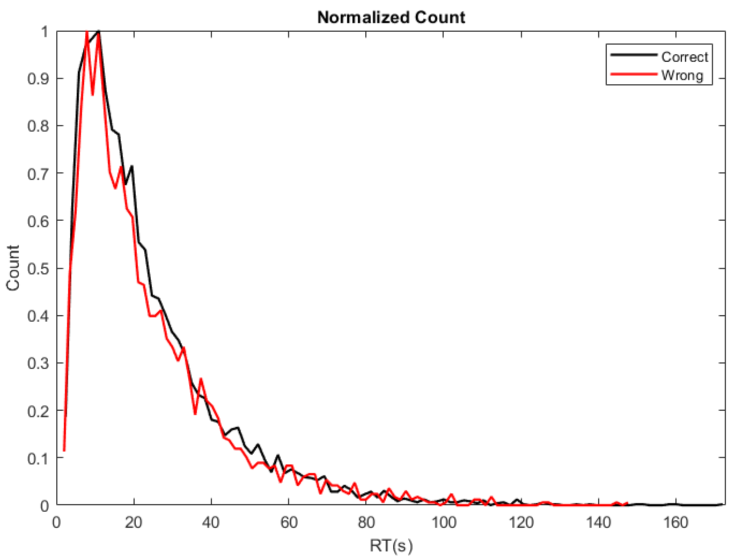

Figure 7: Normalized Histograms of RT values

Question 8

The **race_trial()** function is written and it's available in Functions section. Figure 8 is the winning rate of both the racers with respect to bias of the first racer.

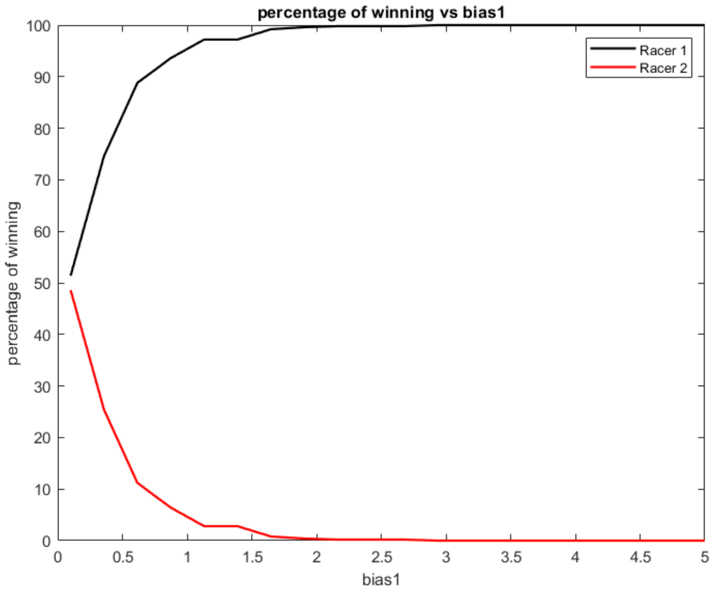

Figure 8: Racing paradigm for differnet values of bias1

Question 9

The code is included in the function section of the .m file. By choosing different maximum duration, we get figure 9. As expected, the number of time that the race reaches the maximum time, decreases as the maximum duration of the race increases. The reason that we expected such thing is that we caclulated the distribution of the RTs in figure 6.

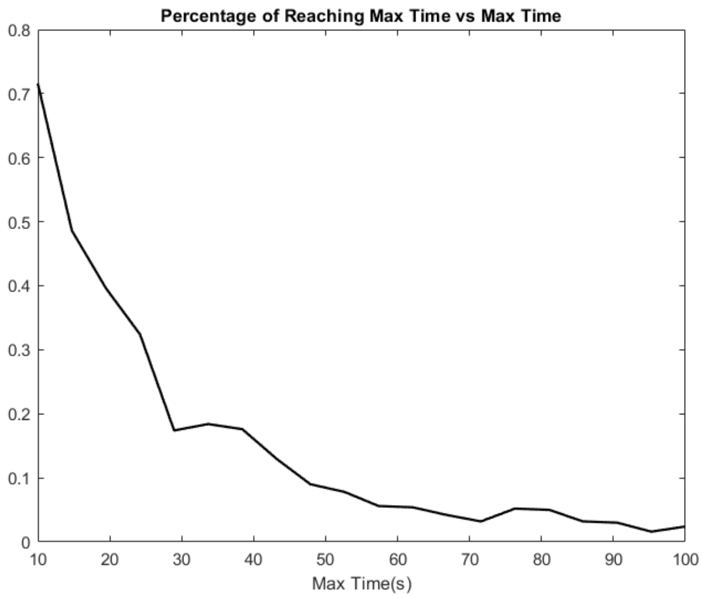

Figure 9: Number of times that the race has reached the maximum duration

Part 2

Question 1

By taking the parameters as,

$$\textbf{MT Probability} = [0.1, 0.05]^T \qquad \textbf{LIP Synaptic Weigths} = [0.1, -0.15]^T$$

$$\textbf{LIP Threshold} = 50$$

We get figure 10. The weight of the LIP inhibitory synapse is more than the excitatory one to be able to see the effect of inhibition.

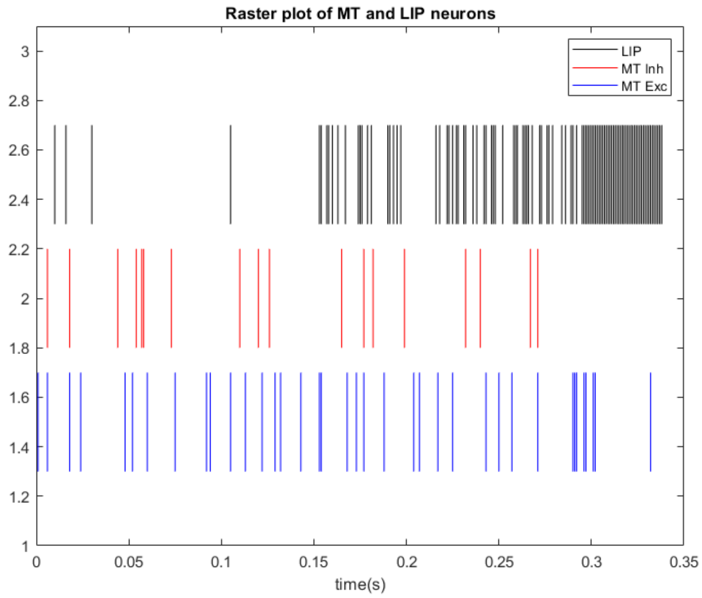

Figure 10: Effect of excitatory (blue) and inhibitory (red) MT neurons on a LIP neuron

It can be ovserved that in the first few milliseconds that we have more inhibition, the LIP neuron does not fire Until the excitation overcomes inhibition and LIP neuron basically takes a decision.

Question 2

First, we modulate activity of MT neurons based on some orientations. Figure 11 shows these orientaions.

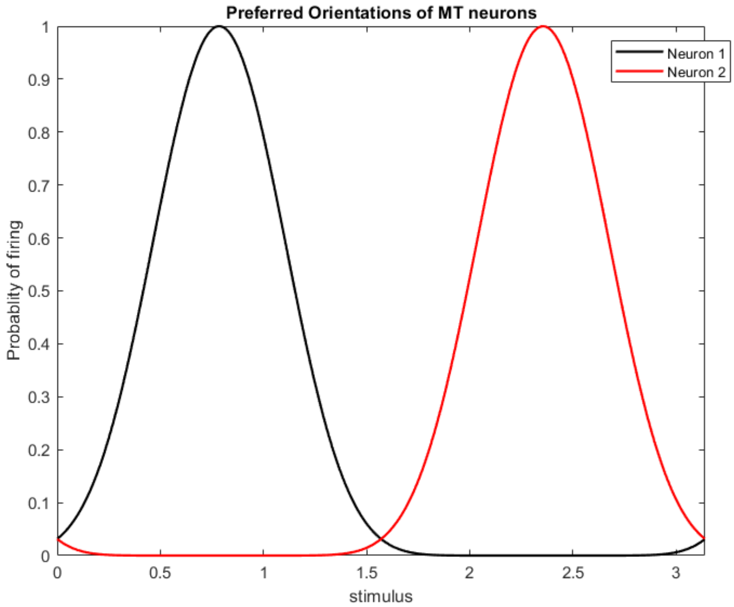

Figure 11: Probabality of the activations of neuron

So we can change the orientations in the model in time and modulate the activity of individual neurons. Figure 12 is a simulation of the model with the parameters:

$$\textbf{activation neuron 1} = sin^{10}(x + pi/4) \quad \textbf{activation neuron 2} = sin^{10}(x - pi/4)$$

$$T = 0.5s \quad \textbf{LIP weights} = [0.1, -0.1]^T \quad \theta_1 = \theta_2 = \pi/2 \quad \text{(constant)}$$

We can see that when the MT1 (red) is more active than MT2 (blue), LIP1 will be activated and vice versa.

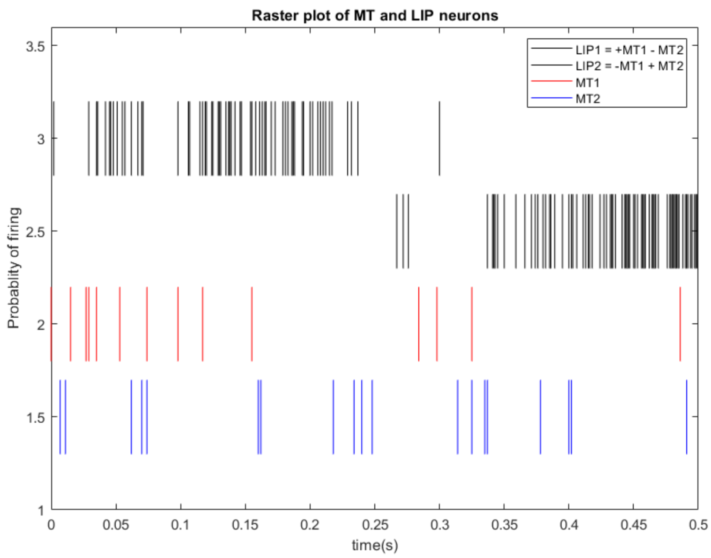

Figure 12: Raster plot of neurons.

In another simulation, we take $\theta_2 = 1.7$ and we change θ_1 from 0 to $\frac{\pi}{4}$ which is the most preferred sitmulus. Figure 13 shows this paradigm. We can see that at first, when $MT2 > MT1$, the second LIP neuron fires more and when the $MT1$ increases enough, it will inhibit LIP2 and causes LIP1 to fire.

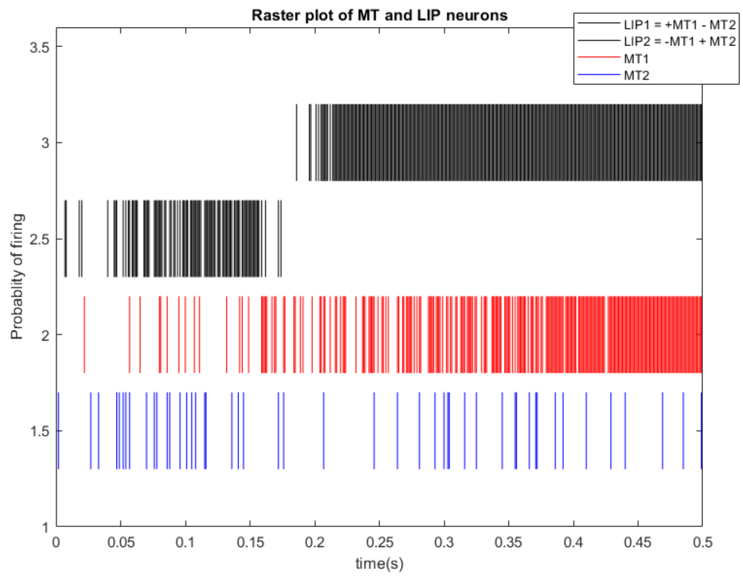

Figure 13: Raster plot of neurons.

Another simulation can be seen in figure 14.

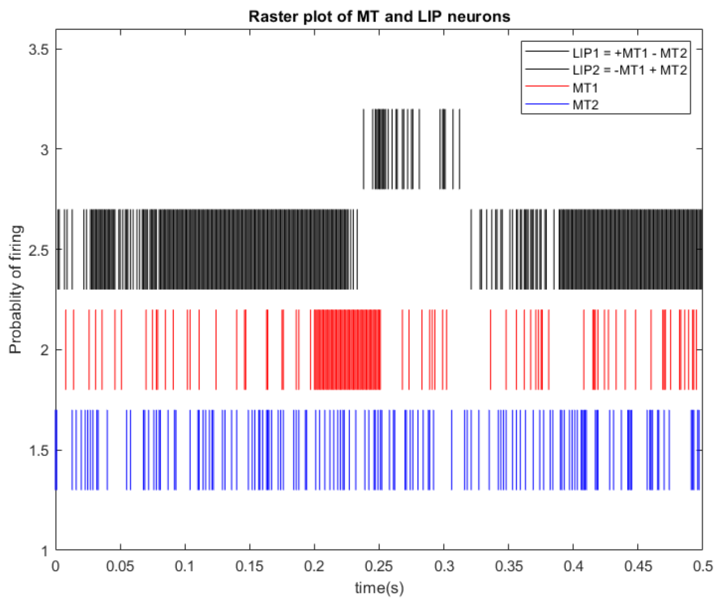

Figure 14: Raster plot of neurons.