Sharif University of Technology
Electrical Engineering School

Advanced Neuroscience HW7
Based on Ratcliff 1978, Shadlen & Newsome 2001

EVIDENCE ACCUMULATION

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Part.1 - Drift Diffusion

Part.1.1 - Simple Model of Drift Diffusion

A function named, "simple model" is implemented using the DDM equation:

$$dX = Bdt + \sigma dW$$

Figure 1: Diffusion Drift Model

The function accepts bias term, dt, sigma and the time interval and returns the choice.

Part.1.2.1 - Distribution of Final Evidence Values

Here, we modify the "simple model" function to return the x (evidence value), too. Then we plotted the distribution of the final evidence values for 10000 1 second trials:

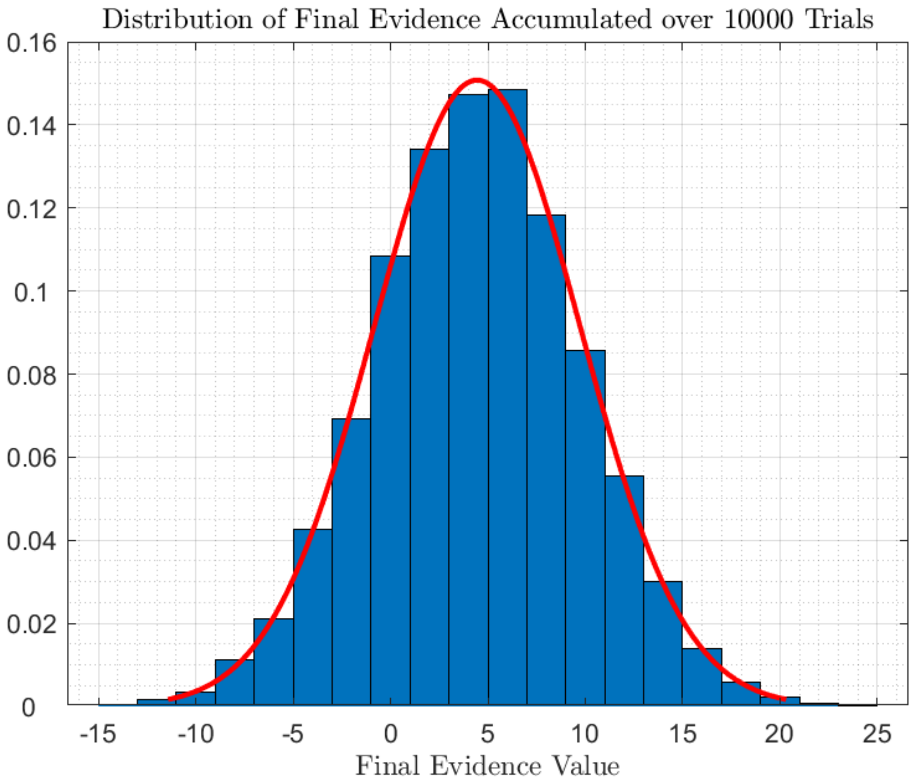

Figure 2: Distribution of Final Evidence Values over 10000 Trials, B = 1, σ = 1, dt=0.1

As you can see, the distribution is a Gaussian distribution. It's logical since dx is calculated using dW which comes from a Gaussian distribution with mean of zero and variance of dt.

Part.1.2.2 - Bias Value Effect on Evidence Accumulation

Here, keeping the previous parameters, we try these different values for bias (B = -1, 0, 0.1, 1, 10) and look for the effect of bias value on evidence plots :

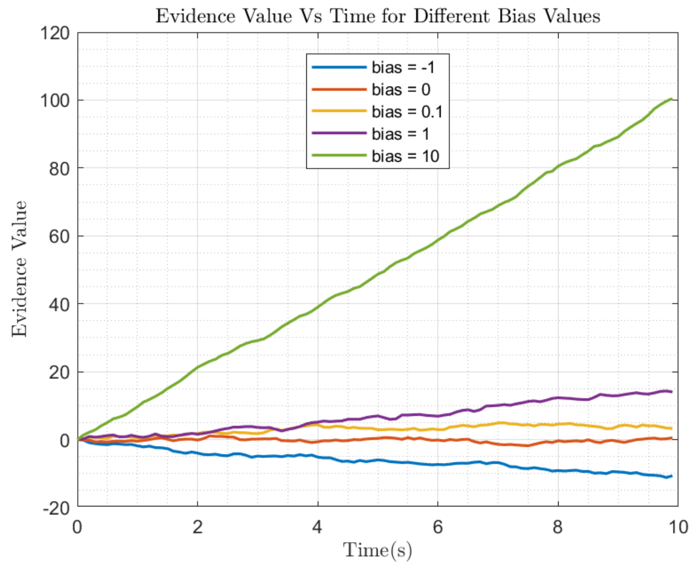

Figure 3: Bias Value Effect on Evidence Accumulating

As you can see, by increasing the bias value, there would be more accumulated evidence since a bias is added in each step to our X(Evidence).

Part.1.3 - Time Interval Effect on Error

Here we run the simulation for different time intervals ranging from 0.5s to 10s long. A choice is chosen to be right if it has the same sign with the bias term. To prevent random noise in our calculation, we run 1000 iterations for each time interval and averaged over the errors.

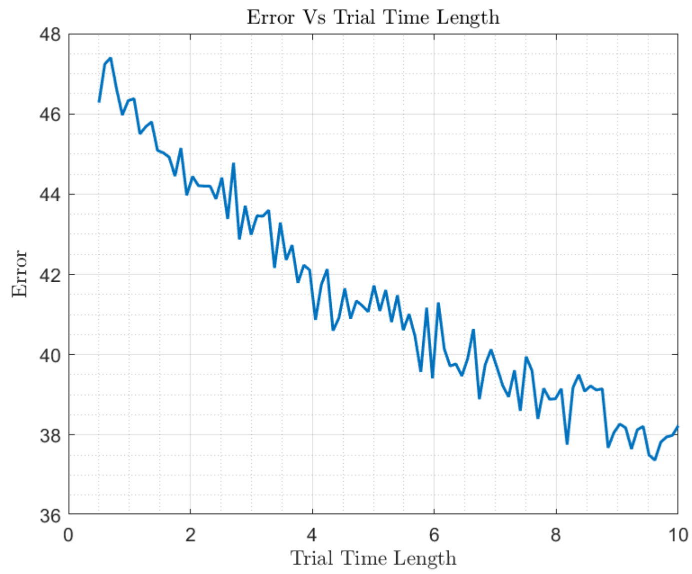

Figure 4: Time Interval Effect on Error, B = 0.1, σ = 1, dt=0.1

As we expected, by increasing the length of each trial, we will have less error.

Part.1.4 - Probability Distribution of Decision Variable

First, we calculate mean and std of the variable X in theory:

$$dX = Bdt + \sigma dW$$
$$\text{X + C = B} \int dt + \sigma \int dW$$
$$\mathbb{E}(X) = \text{Bdt, Var(X)} = \sigma^2 dt$$

As theory says, expected value of evidence should be a linear function and its std is a sqrt function. Now we simulate for 10000 trials each 10s long with B = 0.1, σ = 1, dt = 0.1. Here's the result:

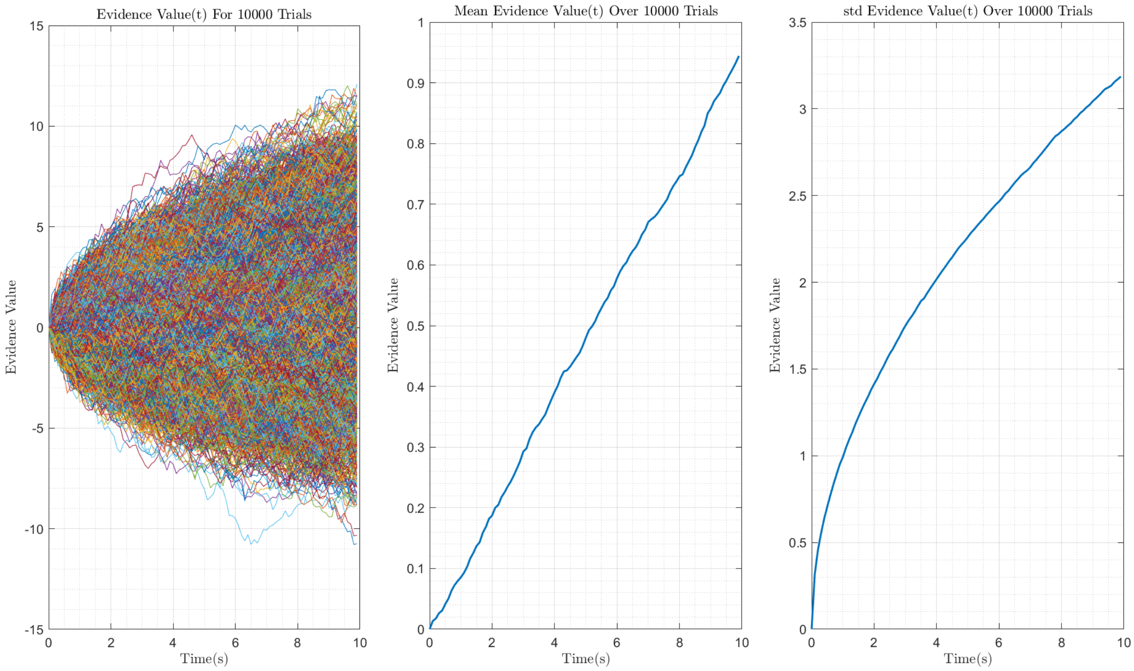

Figure 5: Evidence Vs Time for 10000 Trials, Mean of Evidence(t), Std of Evidence(t)

Simulations match with the theory calculations.

Part.1.5 - Theoric Implementation Using the Distribution of Evidence

Using the CDF of X, we can calculate being below or above the starting point at each trial: As you

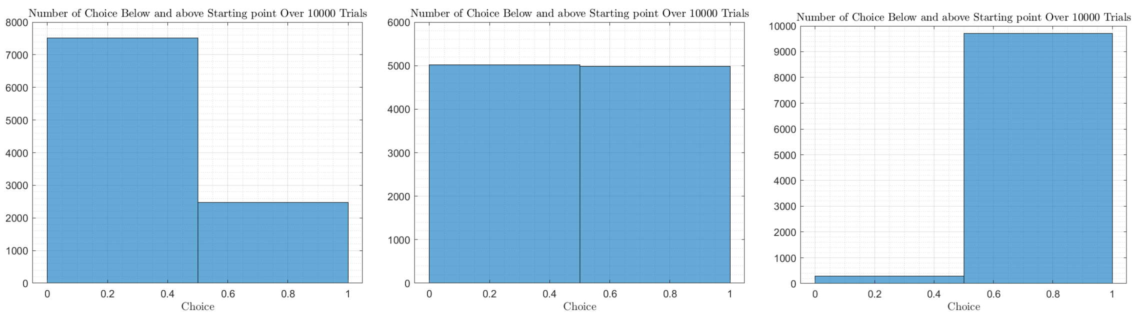

Figure 6: Histogram of Choices in 10000 trials, B = 0.1, σ = 1, dt=0.1, starting point = -0.2, 0.01, 0.6

can see, by increasing the starting point value, we will have more choices below the starting point.

We will have equal number for both choices if starting point is equal to the mean of the distribution which is 0.01.

Part.1.6 - Two Choice Trial

Here we right a function for a drift diffusion with a threshold and unfixed time interval, a choice is given depend on which threshold our drift reaches.

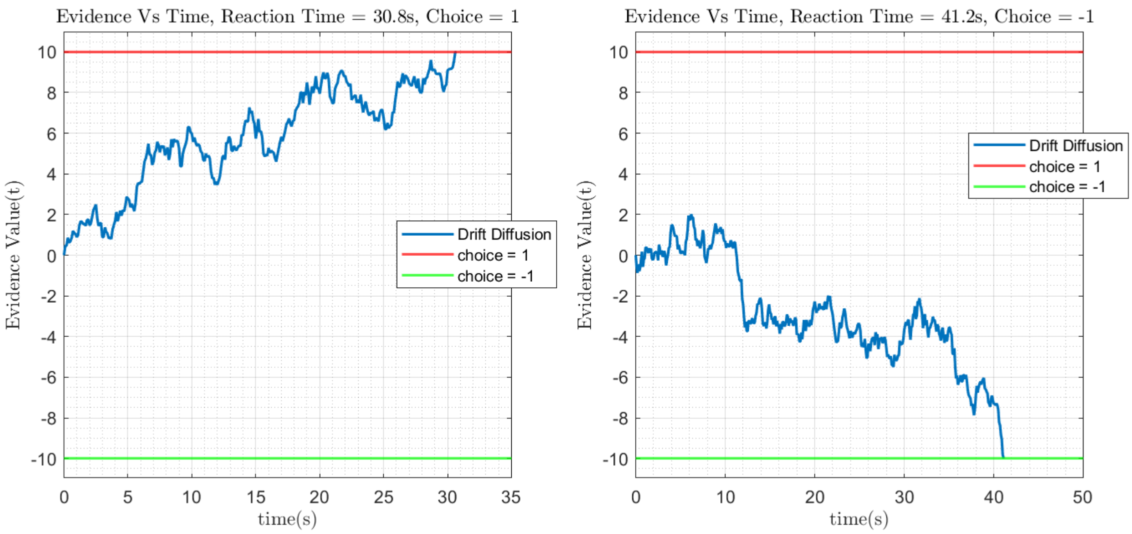

Figure 7: Drift Diffusion, B = 0, σ = 1, dt=0.1, starting point = 0

By changing the starting point and putting them close to the thresholds, our drift will mostly reach the closer threshold.

Part.1.7 - Error & Reaction Time Relationship

It seems that true choices have less reaction time than false choices:

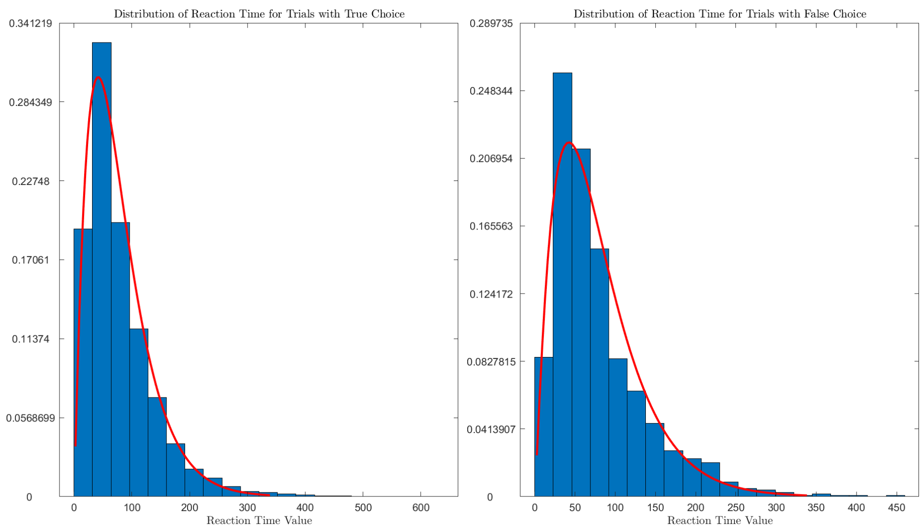

Figure 8: Reaction Time Histogram for True and False Choices

As we've seen in the lectures, the reaction time distribution comes from a inverse Gaussian distribution.

Part.1.8 - Race Diffusion Model

As you can see, the first drift diffusion which reaches the threshold, will win the race and the choice would be that one.

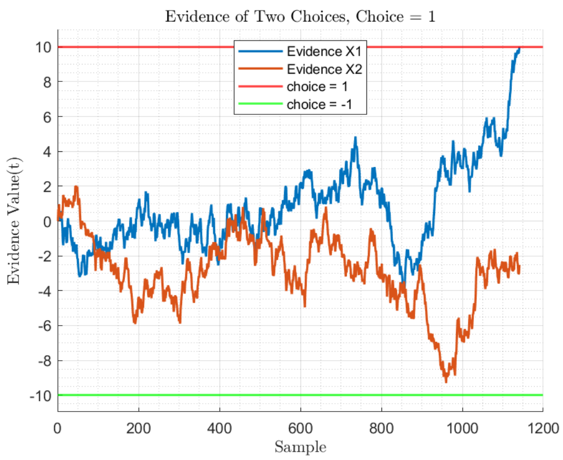

Figure 9: Two Trials of Race Diffusion model

Part.1.9 - Fixed Interval Race Diffusion Model

Here we fix the time interval of the simulation to 20 seconds, the choice with bigger absolute evidence will be chosen. If the evidence for two of the choices were the same, a choice will be selected randomly.

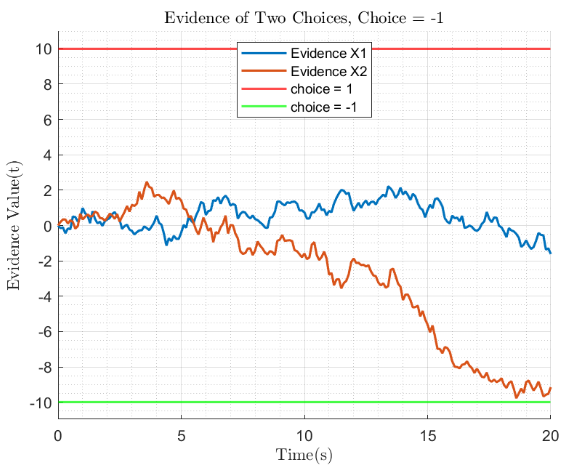

Figure 10: Two Trials of Race Diffusion Model with Fixed Time Interval

Part.2 - a Model for Interaction between MT & LIP

Part.2.1 - Two MT, one LIP network

Here we have two MT neurons which one has excitatory axon to LIP neuron and one has inhibitory axon ot LIP neuron. By setting the weights to 0.1 and -0.12, the probability of firing for MT neurons to 0.1 0.05, and the firing rate threshold to 200, we simulate the code. The condition of spiking for LIP neuron is a minimum accumulated threshold which 5:

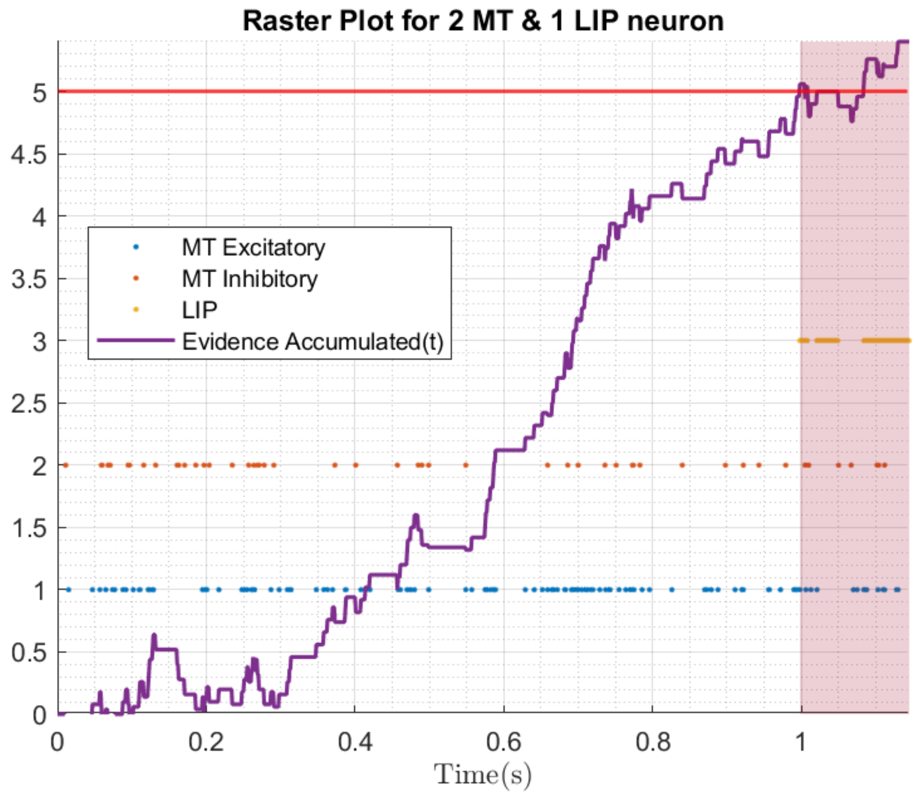

Figure 11: Raster plot of MT & LIP Neurons, Evidence Accumulated By LIP Neuron

Part.2.2 - Two MT, Two LIP network, With Orientation Tuning Stimulus

Here, we create two tuning curves for our two MT neurons as you can see below:

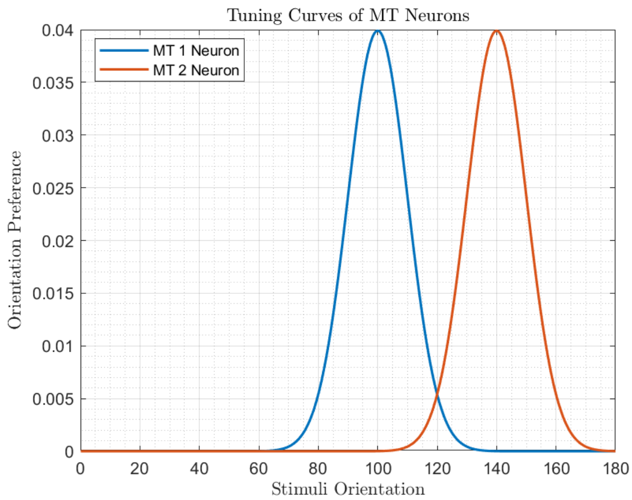

Figure 12: Tuning Curves of MT neurons

The first neuron has the maximum sensitivity to 100 degrees, and the other to 140 degrees. We use this tuning curves as the probability of firing for our MT neurons. Here are the results for different combination of weights between neurons:

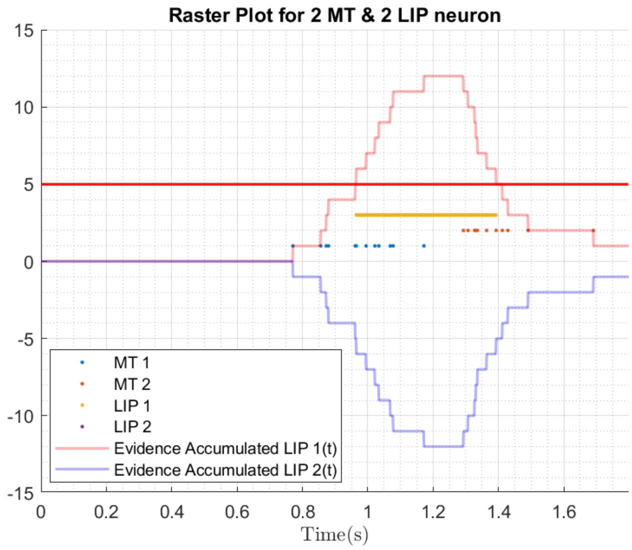

Figure 13: Activity of All Neurons, Evidence Accumulations of LIP Neurons, W11 = 1, W12 = -1, W21 = -1, W22 = 1

As you can see, by increasing the firing rate in MT1, the evidence accumulated for LIP 1 increases and for LIP2 decreases because of the weights between MT1 and LIP1& 2. When the MT2 starts firing, since MT1 don't fire any longer and because of the weights, the evidence accumulated for LIP1 will decrease and for LIP2 will increase. So, in this period, when the evidence accumulated for LIP1 is more than the threshold, the LIP1 fires and since the LIP2's evidence is always below the threshold, it doesn't fire at all in this trial.

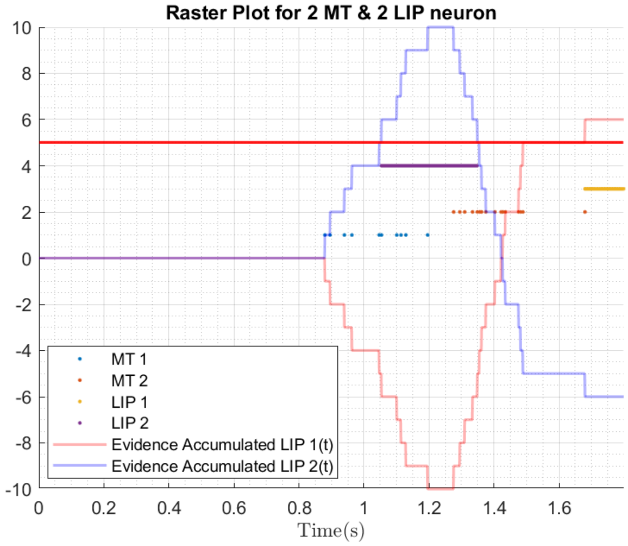

Figure 14: Activity of All Neurons, Evidence Accumulations of LIP Neurons, W11 = -1, W12 = 1, W21 = 1, W22 = -1

Here the weights are inverse of the previous trial, so we expect inverse result. As you can see, at first, the evidence of LIP2 increases and LIP1 decreases by MT1 Activity and when crossing the threshold LIP2 starts firing. When MT2 starts firing, evidence of LIP1 increases and LIP2 decreases. This time, Evidence of LIP1 has reached the threshold so we have a little activity of this neuron, too.

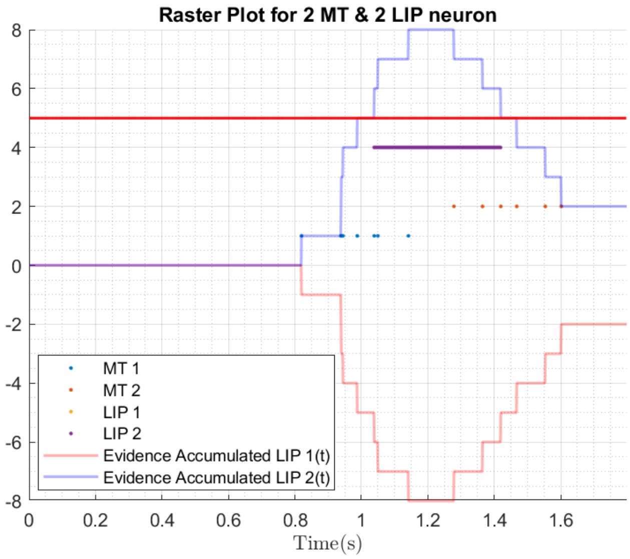

Figure 15: Activity of All Neurons, Evidence Accumulations of LIP Neurons, W11 = -1, W12 = 1, W21 = 1, W22 = -1

Example of LIP1 evidence not reaching threshold in previous state.