Advance Neuroscience

Motor Control Project

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1 Part I - Minimum Jerk Trajectories and Force Field

1.1 Question 1

We can write,

$$x_1(t) = \sum_{i=0}^{5} a_i t^i = a_0 + a_1 t + a_2 t^2 + a_3 t^3 + a_4 t^4 + a_5 t^5$$

$$v_1(t) = \dot{x}_1(t) = a_1 + 2a_2 t + 3a_3 t^2 + 4a_4 t^3 + 5a_5 t^4$$

$$a_1(t) = \dot{v}_1(t) = 2a_2 + 6a_3 t + 12a_4 t^2 + 20a_5 t^3$$

By inserting $t = 0$ initial values,

$$x_1(0) = 0 \Rightarrow \boldsymbol{a_0 = 0} \quad v_1(0) = 0 \Rightarrow \boldsymbol{a_1 = 0} \quad a_1(0) = 0 \Rightarrow \boldsymbol{a_2 = 0}$$

And finally using $t = 0.5$ initial values,

$$x_1(0.5) = 10 \Rightarrow 0.5a_1 + 0.5^2 a_2 + 0.5^3 a_3 + 0.5^4 a_4 + 0.5^5 a_5 = 10 \quad v_1(0.5) = 0 \quad a_1(0.5) = 0$$

$$\Rightarrow \begin{bmatrix} 0.5^3 & 0.5^4 & 0.5^5 \\ 3 \times 0.5^2 & 4 \times 0.5^2 & 5 \times^4 \\ 6 \times 0.5 & 12 \times 0.5^2 & 20 \times 0.5^2 \end{bmatrix} = \begin{bmatrix} a_3 \\ a_4 \\ a_5 \end{bmatrix} = \begin{bmatrix} 10 \\ 0 \\ 0 \end{bmatrix}$$

$$\boldsymbol{a_3 = 800} \quad \boldsymbol{a_4 = -2400} \quad \boldsymbol{a_5 = 1920}$$

So the final position equation is:

$$x_1(t) = 800t^3 - 2400t^4 + 1920t^5$$

Figure 1 is the simulated parameters.

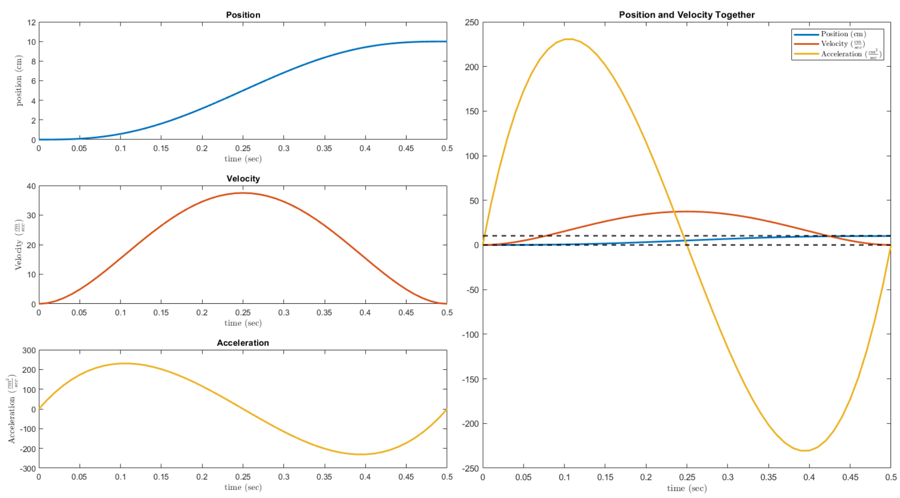

Figure 1

1.2 Question 2

In the curl field forces are perpendicular to the instantaneous velocity of the hand[1]. One of them is clockwise (top) and the other one is counterclockwise. The two bottom plots are curl-assist and saddle force fields which are both parallel and perpendicular to the instantaneous velocity.

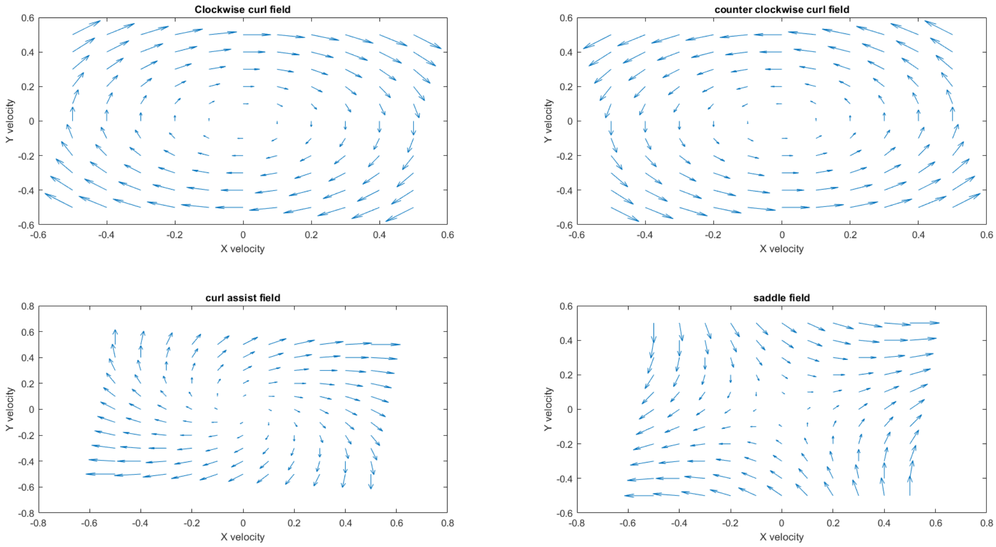

Figure 2

1.3 Question 3

Subjects are supposed to move their hands in a straight line. But the robot applies force to their hands based on the force field. One set of the force fields discussed is always perpendicular to the hand speed. The other set is both parallel and perpendicular.

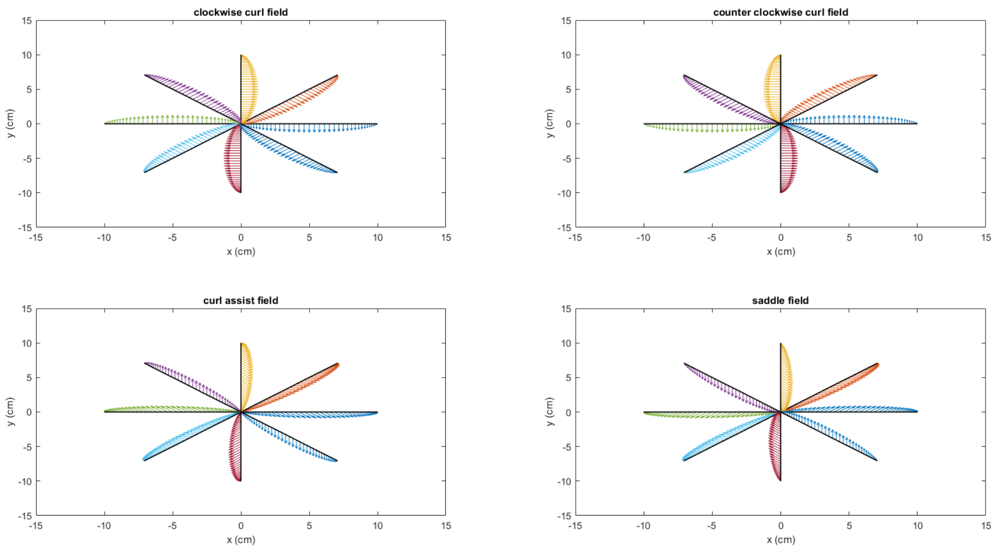

Figure 3

The standard curl field (top left) applies force perpendicular to the velocity and clockwise. The opposite standard (top right) is the same but counterclockwise. The curl assist field (bottom left) is both perpendicular and parallel and is clockwise. The saddle field (bottom right) is also both perpendicular and parallel to the hand velocity and it forces the hand to a specific line which we can see better in figure 2.

2 Part II - Learning Rules in Motor Control

2.1 Question 1 - Relearning Experiment

The initial values of the three models are set to zero. The values of A, B, A_f, A_s, B_f, B_s are set to the suggested values of the referenced paper as below:

$$A = 0.99, \quad B = 0.013, \quad A_f = 0.92, \quad A_s = 0.996, \quad B_f = 0.03, \quad B_s = 0.004$$

The learning occurs in 400 trials. The number of unlearning trials is adjusted so that the output closes to zero at the end of the unlearning period. The total number of trials is 800. The results are shown in figure 4. The overall shape of output is the same in the three models. However, in the Gain-Specific and Multi-Rate models, relearning occurs faster. The Single-State model does not predict savings. The reason that the Gain-Specific and the Multi-Rate models can explain saving, is their internal states ($x_1(n)$ and $x_2(n)$). Although the net output at the beginning of the relearning block is almost zero, the internal states are both non-zero resulting in faster relearning. In the Gain-Specific model, relearning is faster because both up and down states contribute to relearning whereas only the up state contributes to initial learning. In the Multi-Rate model, relearning is faster because, at the start of relearning period, the slow state is already biased towards relearning therefore making the relearning process more dependent on the fast state compared to initial learning.

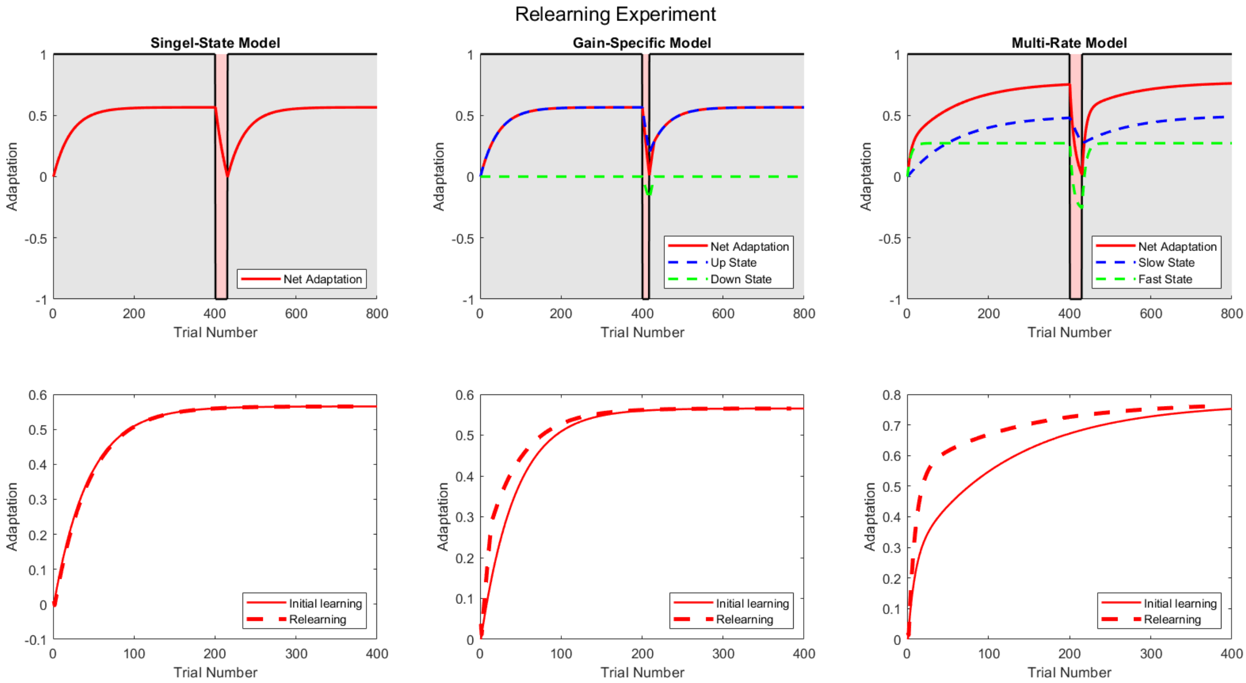

Figure 4

2.2 Question 2 - Relearning Experiment with Washout

1 to 300 washout trials were added to the previous part after the deadaptation trials. The amount of saving versus the number of washout trials is shown in Figure 5. Saving is measured as the percent improvement in performance on the 30th trial in the relearning period compared to the 30th trial in the initial learning period [2]. As expected, the Single-State model does not show saving at all but the two later models indicate saving existence. Also, the amount of saving reduces as the number of washout trials increases because the more the washout trials the less the effect of initial learning.

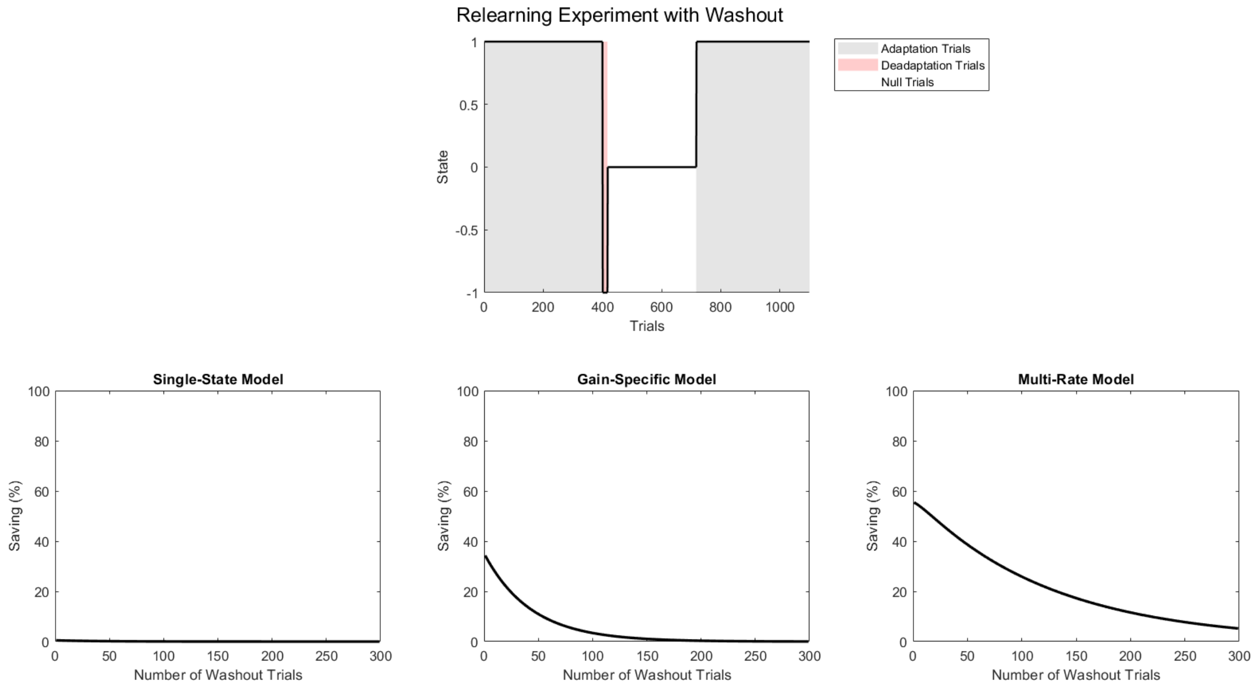

Figure 5

2.3 Question 3

2.3.1 Error-Clamp Experiment

For this part simulation, we set the error values to zero in the error-clamp trials. Figure 6 shows the resulsts. In this case, the motor output of Single-State and Gain-Specific models remains zero. However, the Multi-Rate model predicts a spontaneous recovery. This phenomenon occurs because the fast learning term rapidly decays to zero during the error-clamp period, while the slow learning term decays gradually. The rebound occurs when the fast term decays and the slow term is almost intact and fades when the slow term decays [2].

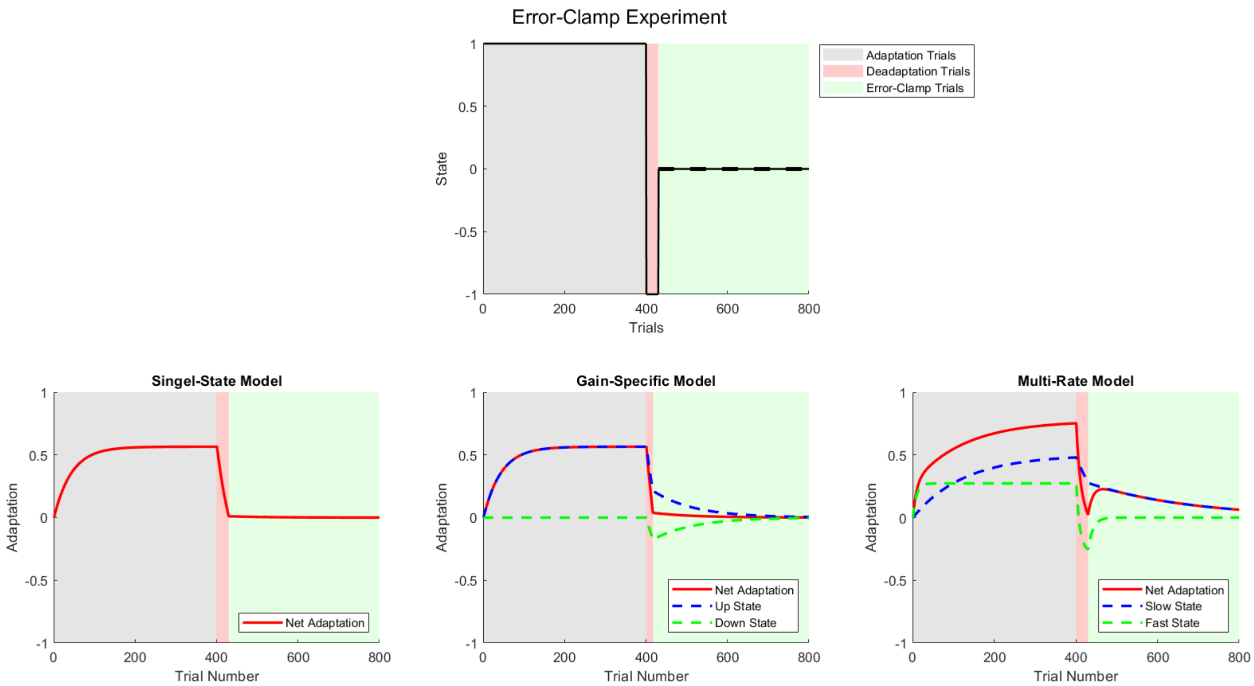

Figure 6

2.3.2 Optional: Symmetric Gain-Specific model, Asymmetric Gain-Specific model, and the Multi-Rate model

An extension to the Gain-Specific model is to change the learning rate and the retention factor of the two internal states. It closely resembles the Multi-Rate model in the number of parameters and the meaning of the parameters.

To compare the Asymmetric Gain-Specific model with Multi-rate model, we evaluated the models output to two different Error-Clamp experiment paradigms See Figure 7. In the first row of Figure 7, both the Asymmetric Gain-Specific and the Multi-Rate model show the rebounding and they both show it in the similar direction with the initial learning (Here positive direction). However, when the paradigm has changed so that the initial learning direction is reversed, the Multi-Rate model correctly indicates rebound in the negative direction. In comparison, Asymmetric Gain-Specific models still has a bias toward the positive direction with a small rebound amplitude which is wrong.

To sum up, the Asymmetric Gain-Specific model, fails to predict the rebound correctly because first, it shows two different rebound amplitudes for each direction of initial learning, and second, it does not follow the direction of initial learning.

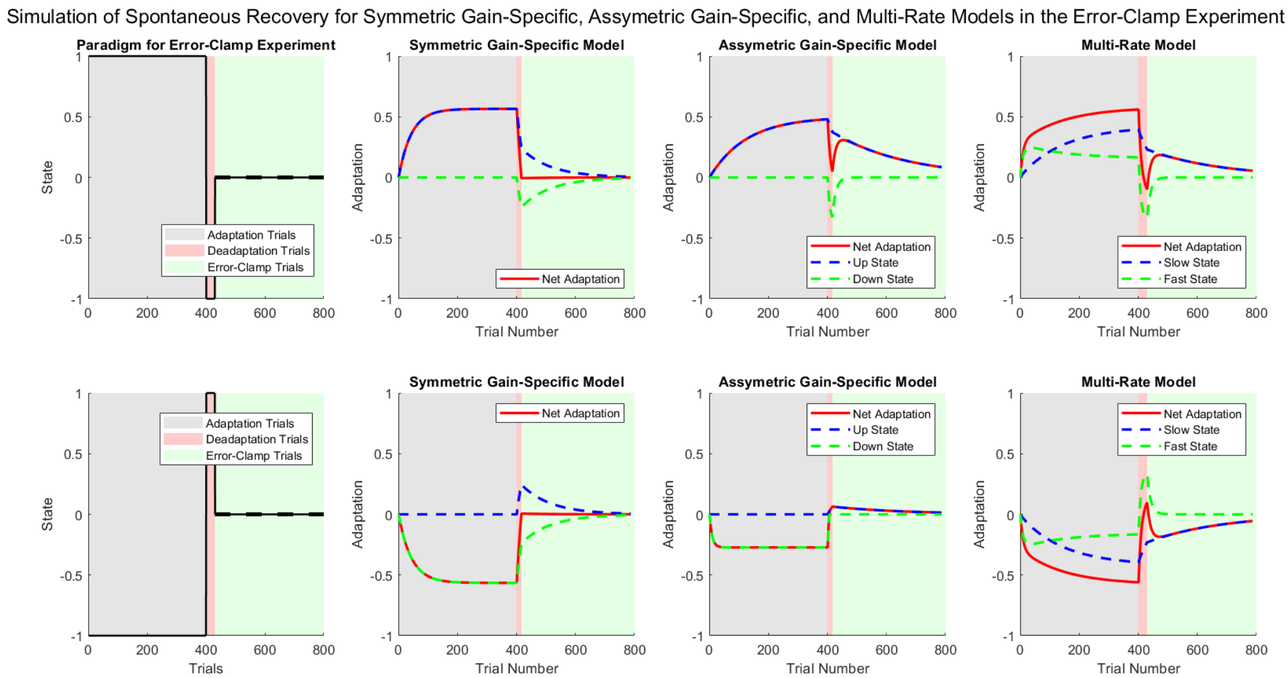

Figure 7

2.4 Question 4 - Error-Clamp/Relearning Experiment

In this part, we added relearning trials after the Error-Clamp trials. See Figure 8. The motor output shows a jump at the beginning of the readaptation trials in the Multi-Rate model, which cannot be seen in the Single-State and Gain-Specific models.

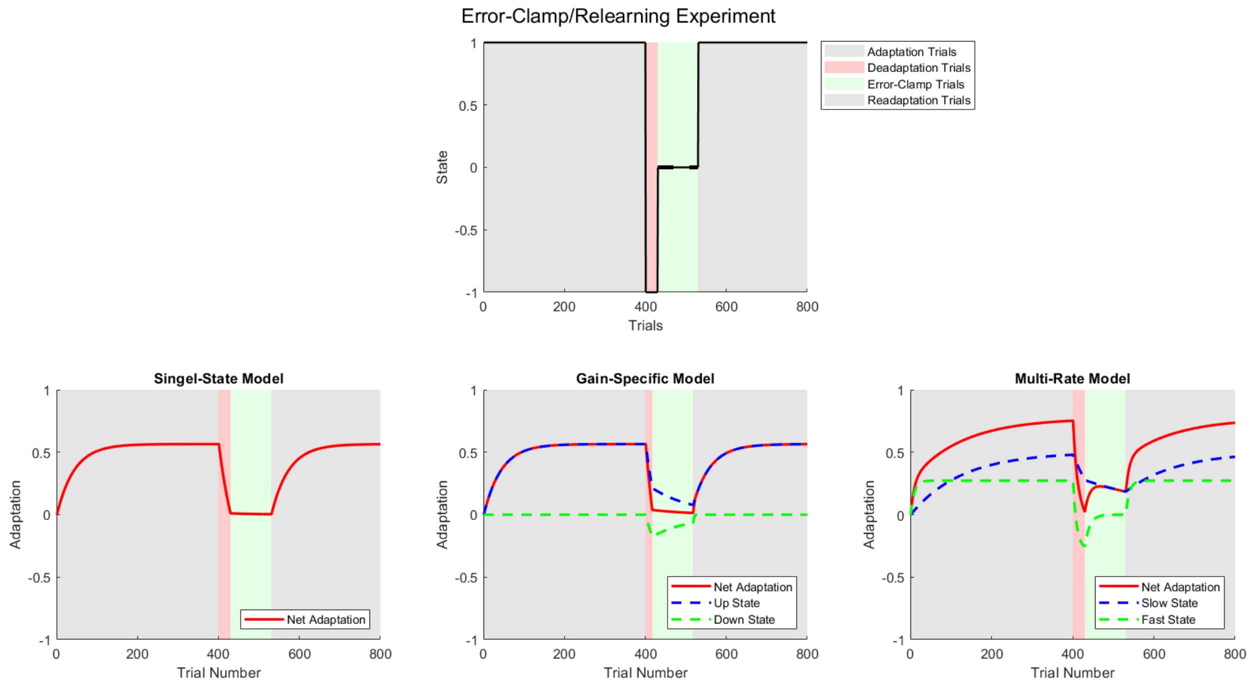

Figure 8

2.5 Question 5 - Anterograde Interference Simulation

The paradigm and the results of this part are shown in Figure 9. According to Anterograde Interference, we expect the time constant for an initial motor adaptation to be faster than the time constant for the subsequent adaptation for the opposite stimulus [2]. The Single-State and the Gain-Specific models cannot predict the Anterograde phenomenon. The Single-State model does not show any changes in the time constant. The Gain-Specific model predicts faster time constants for initial adaptation than the subsequent one, which contradicts the Anterograde interference phenomenon. However, the Multi-Rate model predicts this correctly.

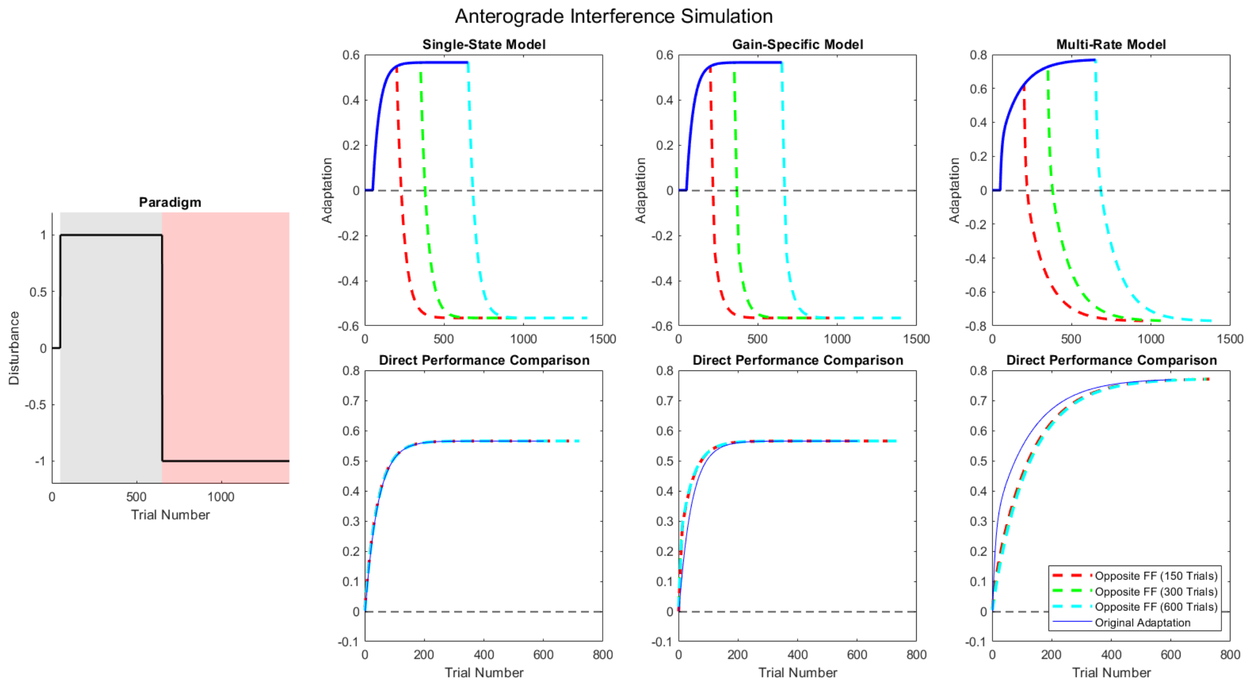

Figure 9

2.6 Question 6

2.6.1 Deadaptation Simulation

Here, after the adaptation trials, the disturbance is set to zero. Figure 10, the top two rows, demonstrate each model's result for three adaptation trials number (300, 500, and 700). We expect that for a longer initial adaptation the model resists forgetting the initial learning. It reduces the time constant. Multi-Rate model predicts this correctly but The Single-State and the Gain-Specific models predict the same time constant for all three.

2.6.2 Down-Scaling Simulation

For this part, the disturbance after the adaptation trials is set to 0.3 (The last two rows of Figure 10). As the deadaptation simulation, we expect smaller time constants for longer initial learning. Again the Multi-Rate model predicts correctly but the Signle-State and the Gain-Specific models show no difference between the three situations.

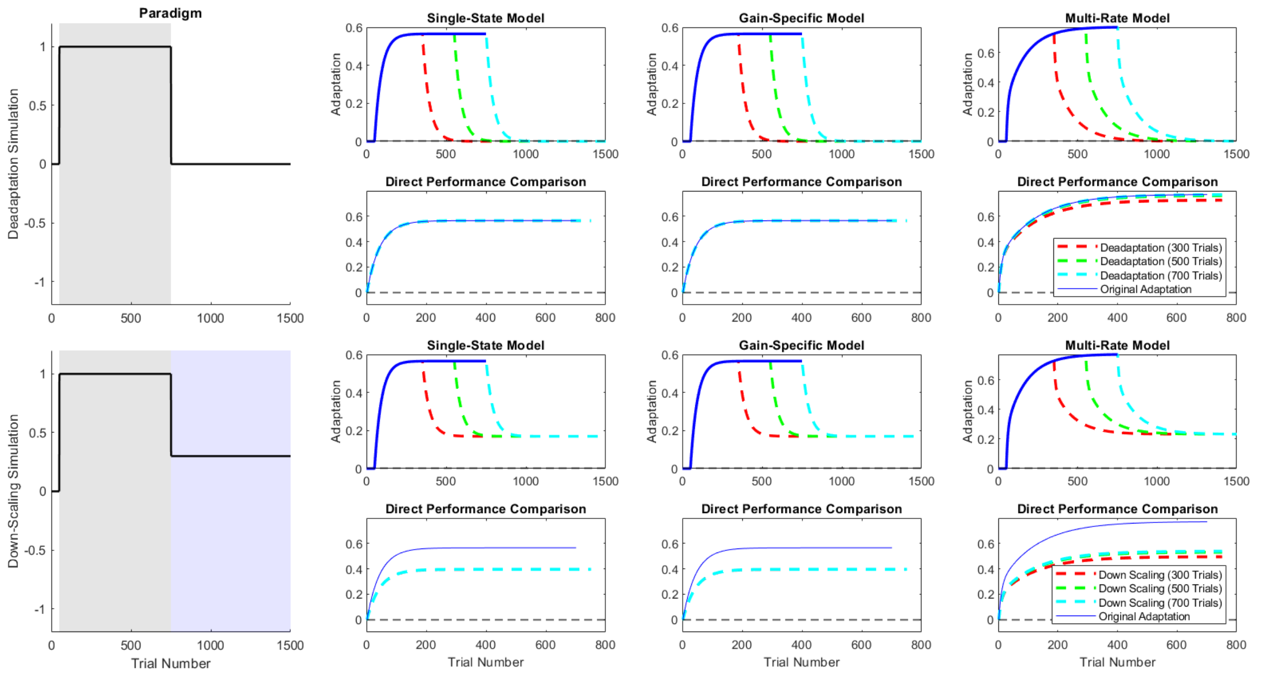

Figure 10

2.7 Question 7 - Parameter variation effect on the amount of spontaneous recovery

As seen in the previous sections, the Multi-Rate model is capable of predicting spontaneous recovery (rebound) in the Error-Clamp trials. It contains four parameters $(A_f, A_s, B_f, andB_s)$ which are designed so that they fit the experimental data the best. Here, to investigate the robustness of the introduced Multi-Rate model, its parameters are varied across the provided ranges. For each, the Multi-Rate model output is calculated as before. The amount of spontaneous recovery is measured as the division of the maximum output value in the Error-Clamp trials to the maximum output value in the initial learning trials [2].

The results are shown in Figure 11.

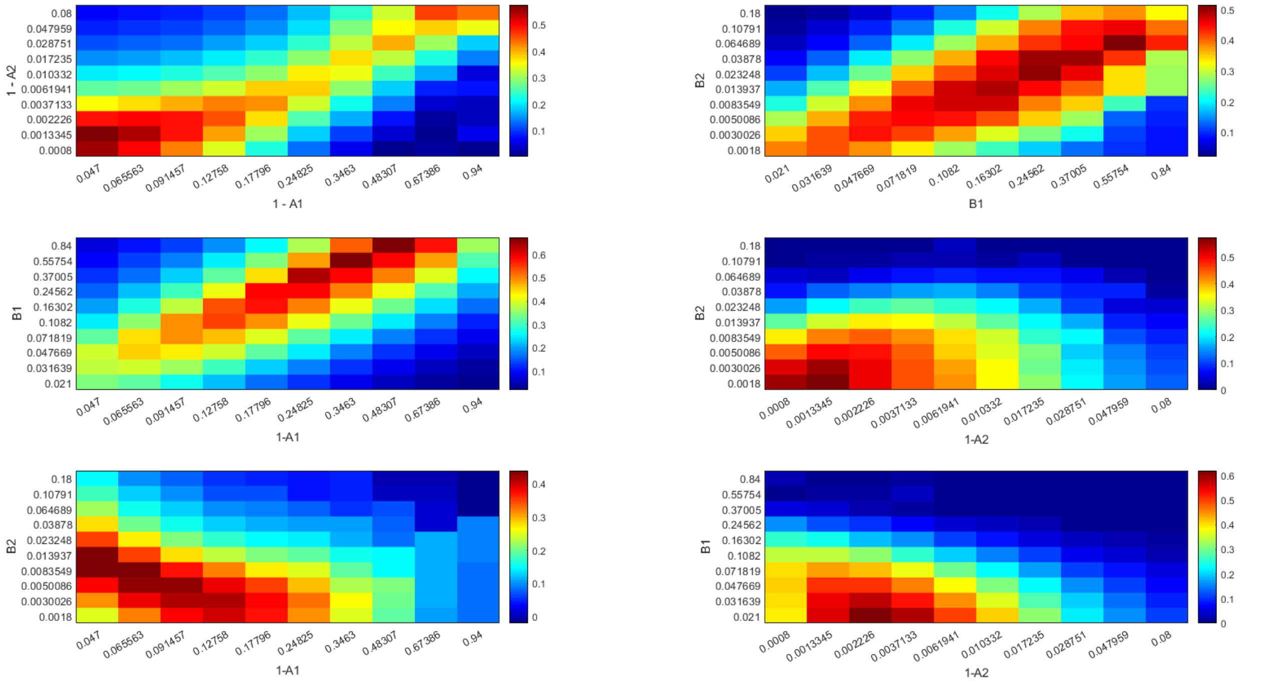

Figure 11

3 Part III - Memory of Errors

First, we introduce the model and the dynamics behind it. This model suggests that the brain stores a previously unknown form of memory, a memory of errors. Classic theories assumed that the brain learns some fraction of the error regardless of its history or magnitude. However, some experiments have shown that the brain can modulate its error-sensitivity and learn more from small errors than large errors.[3]

Introducing the model:
Here the action $u(n)$ is assumed to be 0. So, the model becomes:

$$e_n = x_n - \hat{x}_n \qquad \hat{x}_{n+1} = a\hat{x}_n + \eta_n e_n$$

where,

$$\eta_n = \sum_i w_{i,n} g_i(e_n), \quad g_i(e_n) = e^{-\frac{(e_n - \breve{e}_i)^2}{2\sigma^2}} \qquad and \qquad \boldsymbol{w}_{n+1} = \boldsymbol{w}_n + \beta sign(e_{n-1}e_n)\frac{\boldsymbol{g}(e_{n-1})}{\boldsymbol{g}^T(e_{n-1})\boldsymbol{g}(e_{n-1})}$$

and n is the number of trials.
η is the error-sensitivity and it depends on the error by some weights w_i and basis functions $g_i(e)$. We can imagine the basis functions as a population of neurons that set the error sensitivity based on the current error. Every neuron has a preferred error which is denoted by $\breve{e}_i$ and the activation $g_i(e)$ of the neurons are Gaussian functions with the $\breve{e}_i$ as their mean. By a linear combination of the activity of these neurons, we can calculate the error sensitivity.

Also, the brain is less sensitive to error when the input changes fast[3]. In the model, $\beta sign(e_{n-1}e_n)$ simulates this behavior. The weights increase when the error's sign does not change from trial to trial and decrease when the sign changes at a fast rate. The error sensitivity basis functions are as in figure 12.

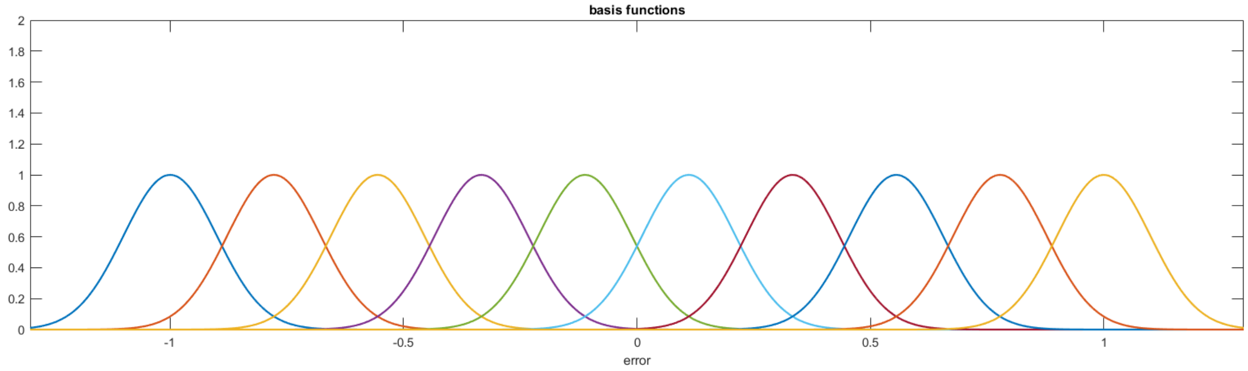

Figure 12

These basis functions are like the tuning curves seen in the V1 area.

3.1 Question 1

The brain learns more from the error when it is consistent in time[3]. This is implemented in the model by η which is error-sensitivity parameter. Equation **(1)** of the reference [3], shows how this parameter affects learning from the error. When η is large (i.e. the model is more sensitive to error) we learn more from the error. We calculate the value of η based on the consecutive error values. So, if this model is the case in the brain, there is a form of a memory of errors in the brain.
Here two simple paradigms are simulated.

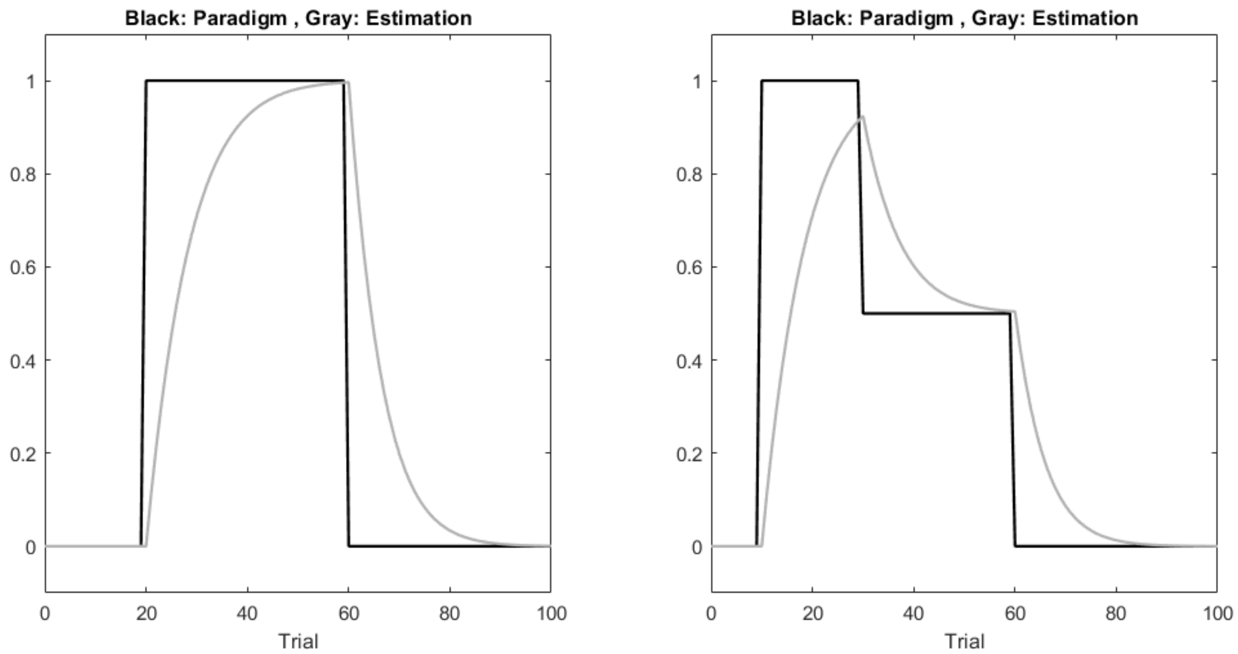

Figure 13

3.2 Question 2

Assume that Z is the probability of staying in the same state. So, for larger Z the environment is more stable. As we discussed before, when the paradigm switches less, we learn faster. When we reduce Z in the model, the states change more frequently. This causes the error to change its sign faster. So the $\beta sign(e_n e_{n-1})$ term makes the learning slower and less. We can see the simulation in figure 14

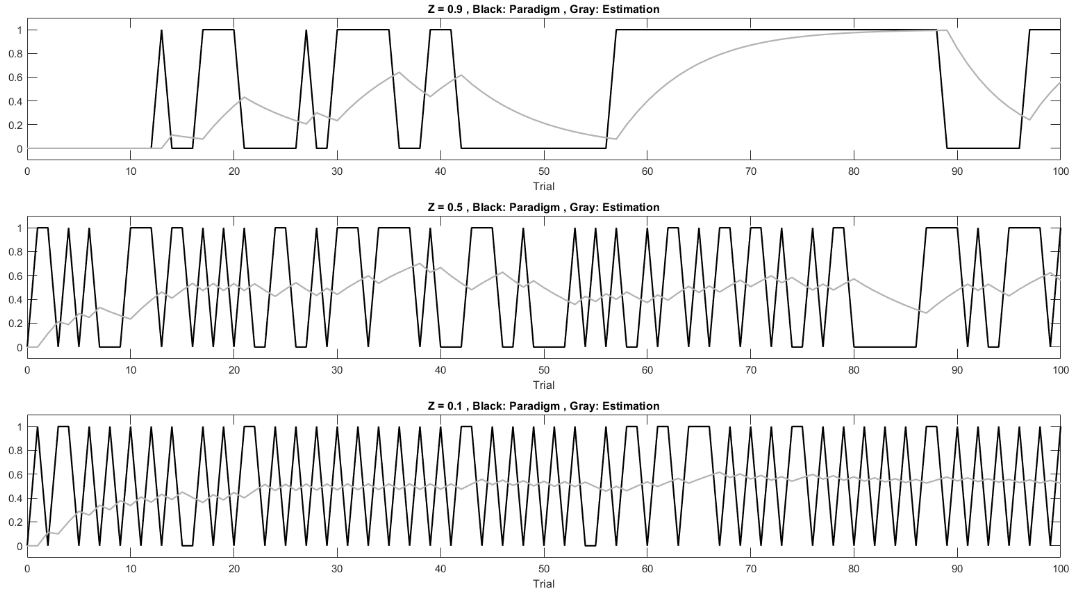

Figure 14

3.3 Question 3

Two demos with $Z = 0.9$ for slow paradigm and $Z = 0.1$ for fast paradigm are included in the project file.
Let two consecutive error values be e_n and e_{n-1}. The paradigm is designed such that:

$$P(sign(e_n) = sign(e_{n-1}) | sign(e_{n-1})) = Z$$

Also, η increases when $sign(e_n e_{n-1}) = 1$. So, as discussed before, we learn more.
We expect that when the error's sign changes rapidly, error sensitivity decreases and vice versa. So, plot 3 in the demo of $Z = 0.1$ decreases over time and the opposite happens in the $Z = 0.9$ paradigm.

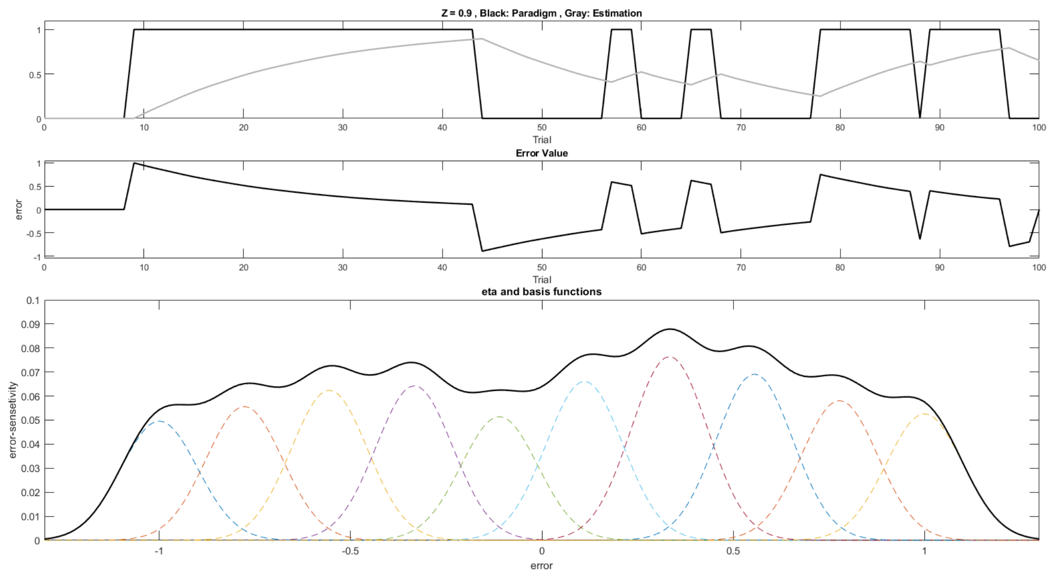

Figure 15: Final parameters of demo for $Z = 0.9$

The heights of the basis functions depend on the value of their weights. (i.e. the dashed curves are $w_i g_i(e)$)

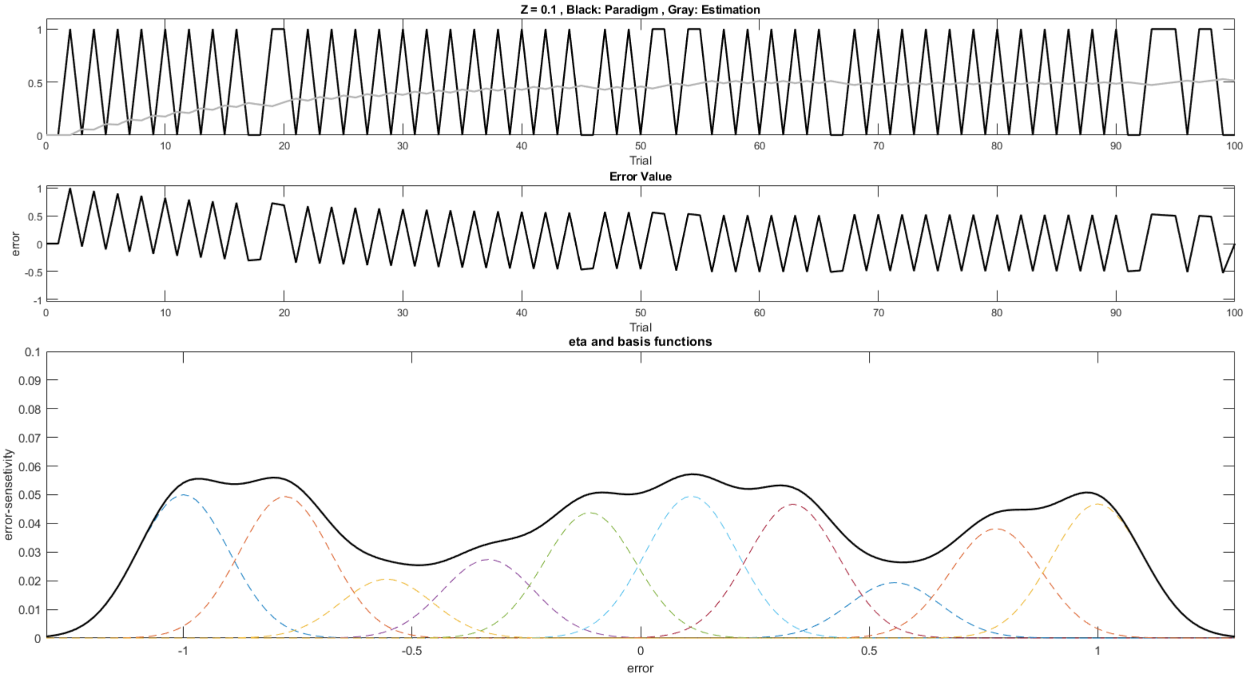

Figure 16: Final parameters of demo for $Z = 0.1$

3.4 Question 4 (Optional)

To further investigate the discussed effect of Z on the error sensitivity, η we plot the error sensitivity over trials for different state probabilities, i.e. Z values. (Figure 17)

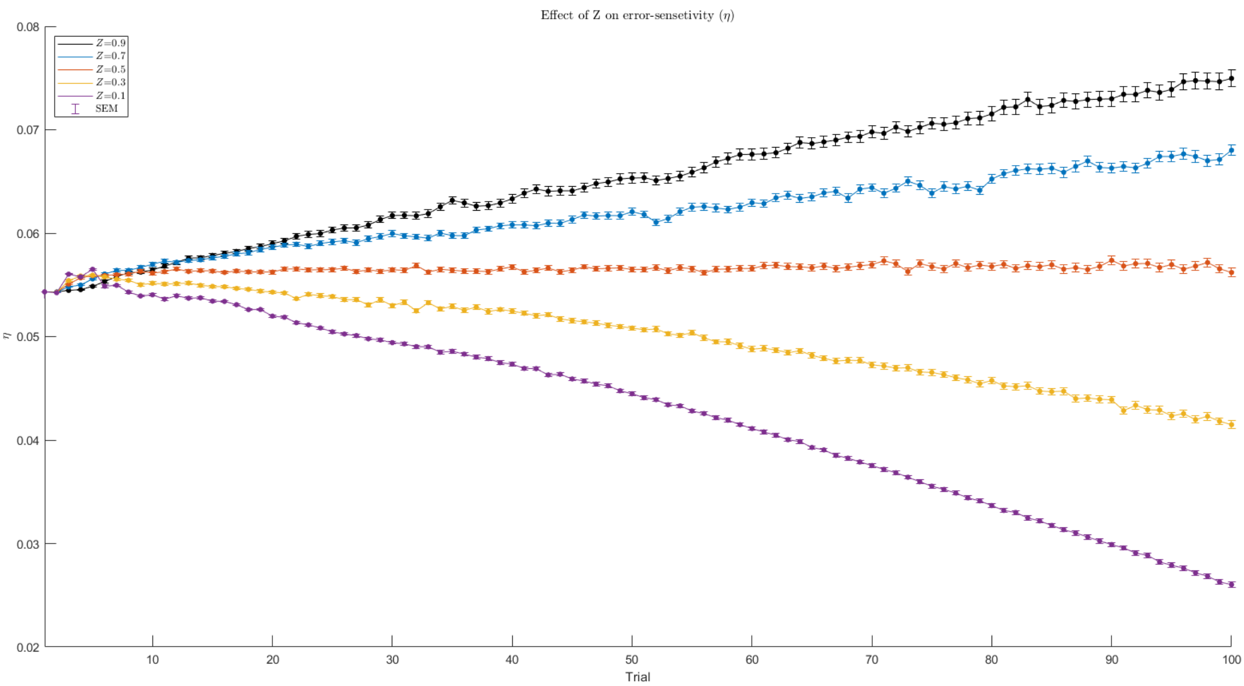

Figure 17

As Z becomes smaller, the error sensitivity decreases.

3.5 Question 5 (Optional)

When we increase the number of trials, the error sensitivity for the value of $Z > 0.5$ diverges very fast but for the smaller Z values, it seems like that they tend to converge after getting smaller than 0 for a small interval. In the $\eta < 0$ interval, the model oposes the error and not only does not learn from the error but also unlearns from it. In fact, the model leanrs in the opposite direction of the error.
It is interesting whether the brain acts like that. If not, it is a weakness of the model. So further research is needed in the area.
Also, the brain may have a maximum to learn from an error. But the model for larger trials diverges. So, it may need some corrections.

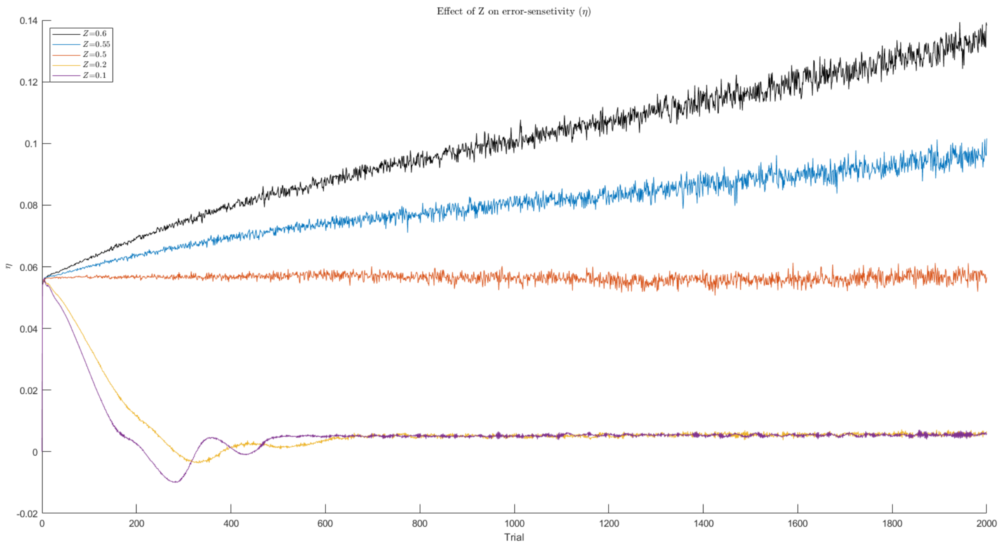

Figure 18

3.6 Question 6 (Optional)

In a paradigm that the value of Z changes over time, we must see changes in the error-sensitivity, η. An example of the paradigm can be seen in figure 19.

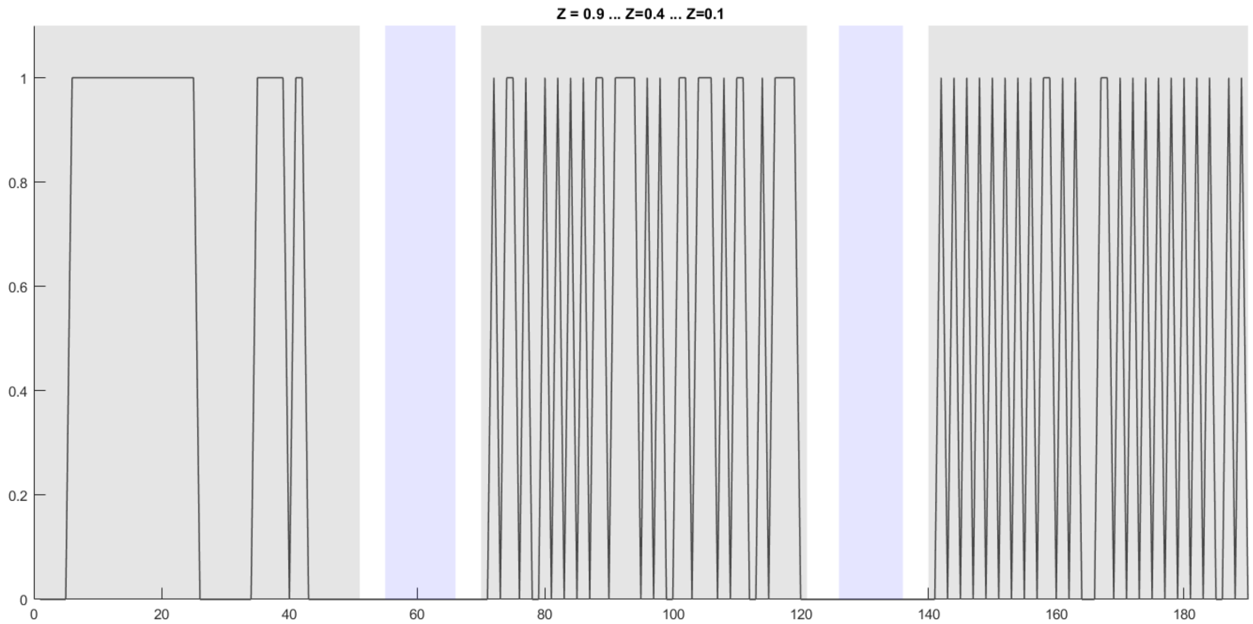

Figure 19

We expect that η rises in the first third of the paradigm. Then falls in the second third and falls with a larger slope in the last third of trials. The simulation is brought in figure 20

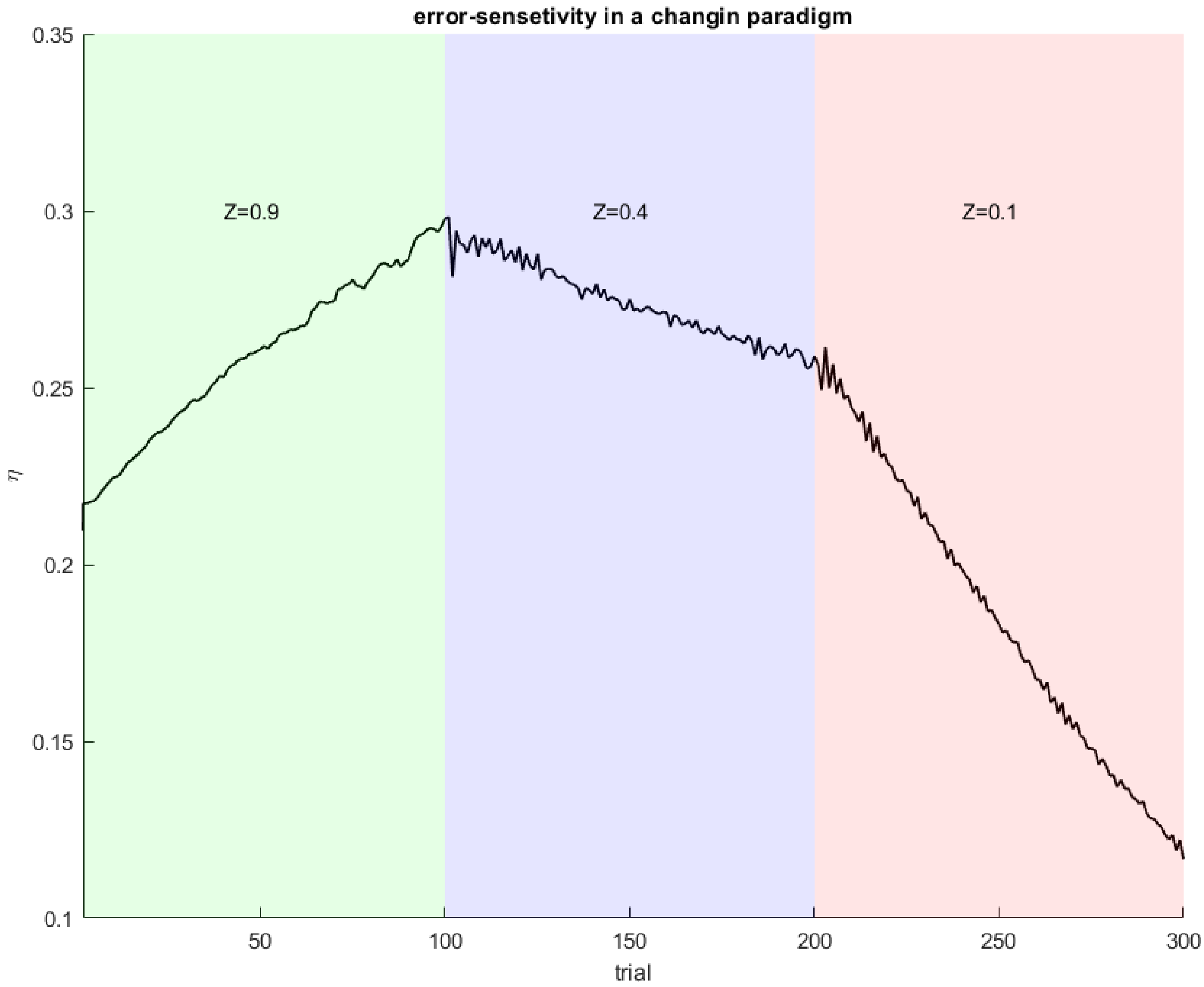

Figure 20

References

[1]: Quantifying Generalization from Trial-by-Trial Behavior of Adaptive Systems that Learn with Basis Functions: Theory and Experiments in Human Motor Control (and supplementary materials), Donchin et al. 2003

[2]: Interacting Adaptive Processes with Different Timescales Underlie Short-Term Motor Learning, Smith et al. 2006

[3]: A memory of errors in sensorimotor learning, Herzfeld et al. 2014