Motor Control

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In order to reach a movement, the brain should map the goal limb motion into some predicted forces through the internal models. the model will adapt considering the changes in the forces. This adaptation and learning can be model with diverse models which each of them predicts some of the features in motor skill while fails to model other features. In this article we first, give a thorough investigation on motor learning and adaptation of internal brain map. (1) Next we try to both introduce and compare different models of motor learning. (2) Finally we will show how much brain can learn from error and the its sensitivity to the frequency of the changes in perturbations. (3)

Motor control | Motor learning | Adaptation | Force field

Motor control is defined as the process of initialing the movement. It appears that brain predicts the up-coming movement and sends motor commands to the limbs in order to create an appropriate movement. One hypothesis is that through practice, the brain builds an internal model of the novel forces. The internal model is a mapping from the arm's position and velocity space into force. (4) In order to reach the goal of understanding the motor control dynamics, studying memory and how it is involved in the motor learning has an essential role. Saving refers to the effect of prior learning on the subsequent learning.

In this article we try to investigate three main topics: Firstly, model straight line hand movement trajectory. This goal is reached by defining the term force fields used in experiments and the mathematical approach for describing the introduced model. Secondly, we are going to study motor learning and its different properties. We will investigate three different models and compare how can they code savings' features in motor leaning. Finally, we are going to consider the effect of perturbations on the amount of saved data using the mathematical approach introduced in(3).

Theory

The article is focus on finding a way to generalized a model straight line hand movement trajectory and understand meaning of force fields used in experiments and their effects. Because human have eight directions they introduce the equation below for i from 1 to 8.

$$y^{(n)} = DF^{(n)} - z^{(n)}$$

$$z_i^{(n+1)} = z_i^{(n)} + B_i k^{(n)} y^{(n)} i = 1, ..., 8$$

Which D, is a 2×2 matrix with m/N and B, 8×8 matrix, is the generalization function(1).

They decided to use a fixed desired trajectory so they used jerk trajectory. As we know that smoothness can be quantified as a function of jerk, which is the time derivative of acceleration. Hence, jerk is the third time derivative of location (i.e., position). If the location of a system is specified by variable x(t), then the jerk of that system is:

$$jerk \equiv \dddot{x} = d^3x/dt^3$$

for CNS to move hand or some other end effector smoothly from one point to another, it should minimize the sum of the squared jerk along its trajectory. For a particularly trajectory x1(t) that starts at time Ti and ends at time Tf we can measure smoothness by calculating a jerk cost:

$$\int_{Ti}^{Tf} jerk^2 \, dt$$

And if we Optimizing the functional above results in:

$$(d^6 x_1(t))/(dt^6) = 0$$

it could be a good choice for a function with zero sixth derivative is a fifth degree polynomial. Sometimes, in Motor Control experiments, there are perturbations in the environment. These perturbations are usually forces proportional to hand velocity magnitude with orientations perpendicular or parallel with velocity's orientation.(or sometimes a combination of these orientations). Model for such force fields in 2 dimensions follow notation below:

$$f = BV = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix} \begin{bmatrix} \dot{x} \\ \dot{y} \end{bmatrix}$$

Which f is force vector generated by the hand, B is field matrix and V is velocity vector.

Results

In this section we simulate two different formulations of memory first one introduces three models and second part represent a model for sensorimotor learning.

Interacting Adaptive Processes. In this section we try to introduce three models of learning. (2)
Single state model(one state):

$$x(t+1) = A.x(t) + B.e(t)$$

Gain specific model(two state):

$$x1(t+1) = min(0, A.x1(t) + B.e(t))$$

$$x2(t+1) = max(0, A.x2(t) + B.e(t))$$

$$x(t+1) = x1(t+1) + x2(t+1)$$

Multi rate model(two state):

$$x1(t+1) = A_f.x1(t) + B_f.e(t)$$

$$x2(t+1) = A_s.x2(t) + B_s.e(t)$$

$$x(t+1) = x1(t+1) + x2(t+1)$$

In these equations e(t) is the error while x(t) is the net adaptation and the terms x1(t) and x2(t) are the two different states of the models. In the multi-rate model the first component is the fast part which response immediately to the input error and the second part is the slow part which hold the learning from the previous errors in memory.

figure1 and 2 show the output of these models to different inputs and how they can code the characteristics of motor movements.

In figure3 we investigate that how the model behaves in the relearning phase. As it is obvious in the figure, the system learns faster while we introduce the opposite error and also slower through downscaling.

Sensorimotor Learning. In this section we introduce a formulation for how the switching rate of noise can effects learning. While the noise switches less often it means that the error consists information about the environment, thus, brain should be sensitive to this input. On the other hand, when the error changes rapidly there is a lower chance of information presence in it, resulting less learning sensitivity to error. Here is the mathematical formulation(3):

$$\eta(e^{(t)}) = \sum w_i g_i(e^{(t)})$$

$$g_i(e^{(t)}) = e^{-(e^{(t)}-\mu)^2/2\delta^2}$$

$$w^{(t+1)} = w^{(t)} + \beta sign(e^{(t)}e^{(t-1)})g_i(e^{(t-1)})/abs(g_i(e^{(t)}))$$

Discussion

Here we first presented a brief description about force field and a single line hand movement, next we presented three models , single-state, gain-specific and multi rate and by comparing these three concluded that the multi-rate model predicts the adaptation which takes place in memory accurately. This two-state model is a sum of a fast and slow sub-models which each one has significant role in a specific section of adaptation. At last we tried to find the sensitivity of the learning process to the rate of changes happens in noise using the equations presented in (3).
In the further studies the effect of the model coefficients in the multi-rate approach can be investigated and show what is the best fit for the real data collected from participants in motor tasks. With the help of the real data we can investigate whether the coefficients have to be constant or is bether to be time-dependent.

Materials and Methods

Modelling. In figure 1 and 2 we used all three models with parameters set at A=0.99 and B=0.013 for the single-state and gain-specific models; and

$$A_f = 0.92, A_s = 0.996, B_f = 0.03, and B_s = 0.004$$

In figure 3 the parameters were set at

$$A_f = 0.75, A_s = 0.996, B_f = 1, and B_s = 0.01$$

In figure 4 we derived the presented formulation for error sensitivity using a two-dimensional vectors with preferred error equal to zero and 0.5 variance for the basis functions.

References

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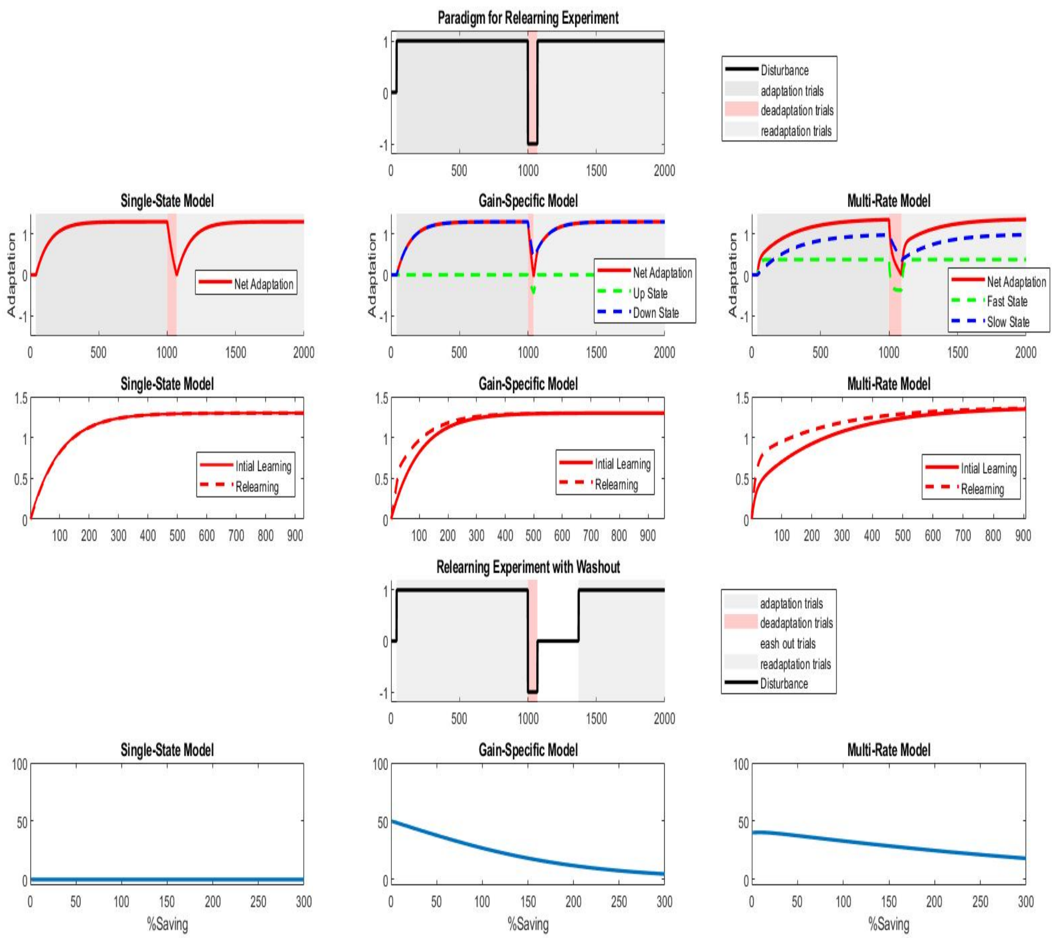

Fig. 1. First row indicates the error presented to different models. In the second row we show the output of different approaches to this error. (the number of deadaptation trials sets so that the net adaptation of each model reaches the baseline value.) In the third row we compare the initial adaptation phase to the readaptation one, as it is shown the learning gets faster in readaptation for both two-state models. In the forth row we introduce the error with washout trials and in the following row we plot the percentage of saving through amount of washout trials. The saving percentage is calculated by the difference of the adaptation in the 40Th trial of readaptation and initial adaptation.

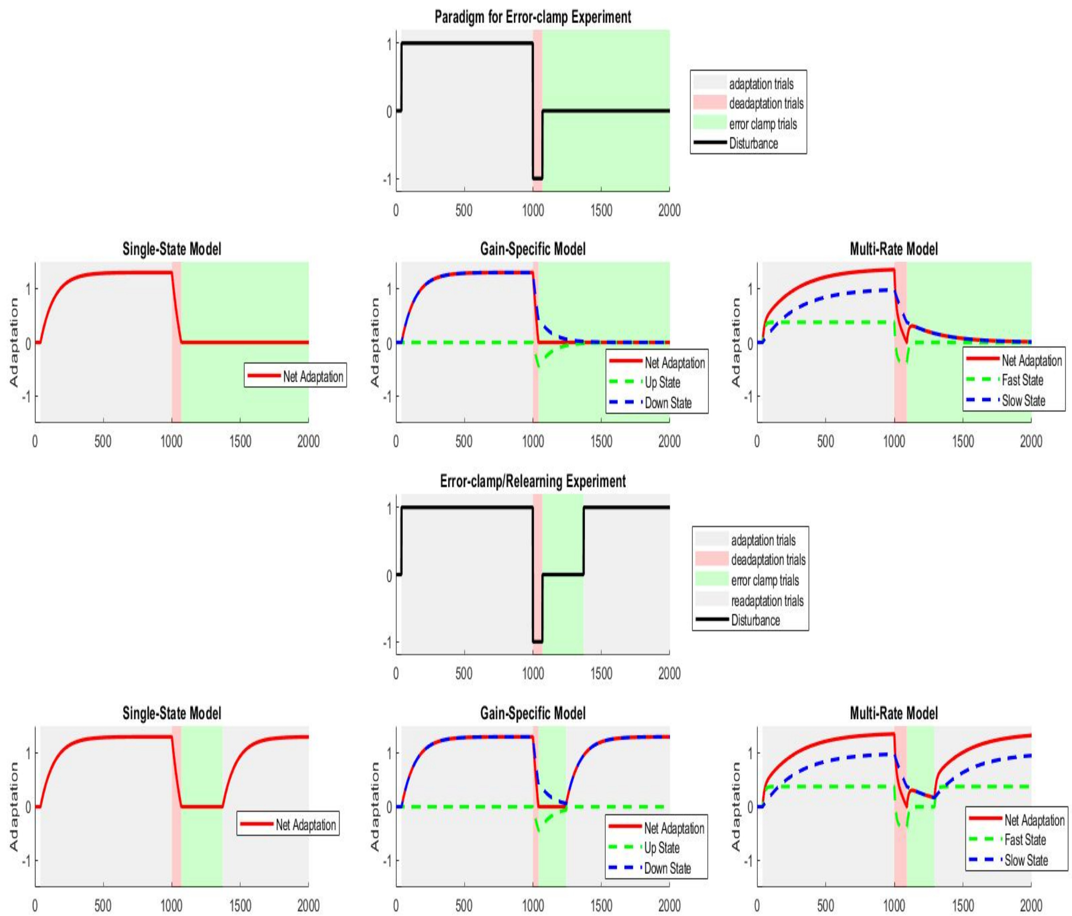

Fig. 2. Here we try to investigate the effect of error-clamp or in the other word washout trials on these models.The first row shows the presented error while the second row indicates the outputs of this error. As it is obvious the multi-rate model holds the savings even during the washout trial in the slow-rate component. The third and forth row are showing the readaptation after the error-clamp trials for all the three models.

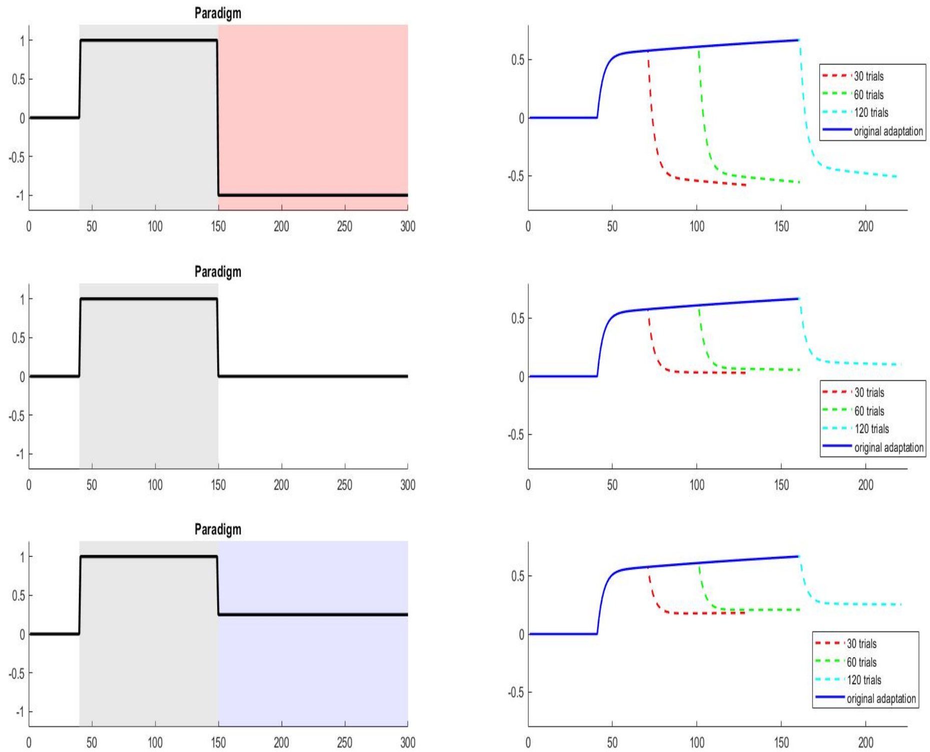

Fig. 3. In this part at first we try to change the parameters of multi-rate model so that the adaptation reaches to the goal amount in an appropriate amount of trials. The first row shows how the multi-rate model predicts the Anterograde interference effect. The second row is predicting the unlearning feature of motor memory and the last row is showing the downscaling characteristic.

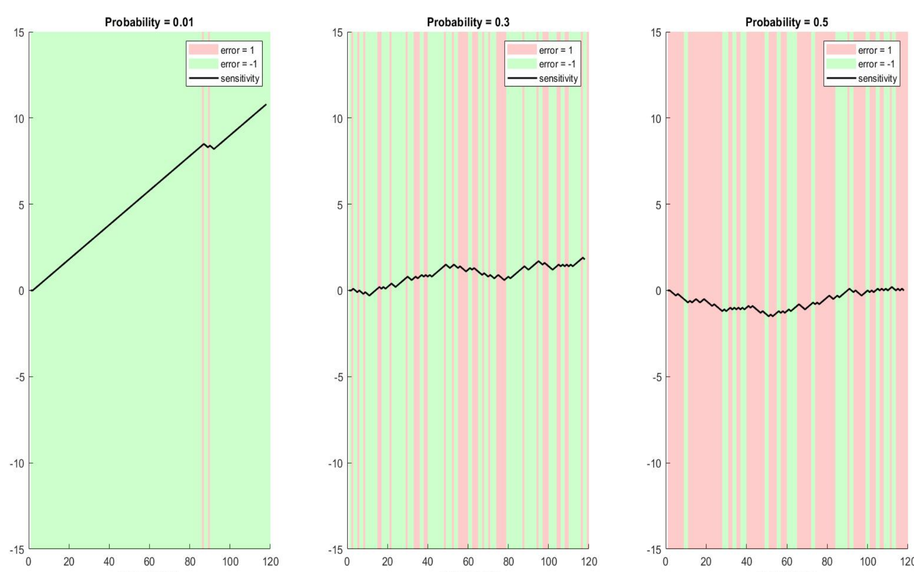

Fig. 4. In this figure we simulate the formulation of memory sensitivity presented in result part. Each column gives an error specified by green and red, and find out the relation between the variance of error and learning from that. As you can see in the slowly switching environment brain learns more from the error as if it is constant in it, while more random error seems to has no information.