Motor Learning Dynamics: An Examination of Single-State, Two-State Gain-Specific, and Two-State Multi-Rate Models

Zahra S. Bahri[a,b], Amirmohammad Mazarei[a,c], and Aliakbar Mahmoodzade[a,c]

[a]Student, Sharif University of Technology; [b]Computer Science; [c]Electrical Engeneering

Disclaimer: **This article is written based on the studies done by Smith MA., Ghazizadeh A., and Shadmehr R. in their** *Interactive Adaptive Processes with Different Timescales Underlie Short-Term Motor Learning* **(1) paper. We repeated their simulations and illustrate here the final results of our own.**

The complexities of motor learning necessitate abstraction for proper understanding, testing, and intervention. This paper delves into three such mathematical models of motor learning: the Single-State Model, the Two-State Gain-Specific Model, and the Two-State Gain-Independent Multi-Rate Model. We meticulously modify various parameters in these models, adding Gaussian and Pink noise to understand the model's stability and implications under noisy conditions, which are analogous to the natural biological environment. We introduce a novel concept of the area between learning and re-learning curves, hypothesizing that a larger area indicates a faster relearning process relative to initial learning. Our findings provide new insights into the dynamics of motor learning and the resilience of these mathematical models under varying conditions.

The Multi-Rate model shows more fluctuations and drifts when exposed to noise, than other models, however it performs much better when coefficients in the model change. The other two models give non-realistic values when their coefficients change outside of a certain range. Since the nature of the brain declares these values to be flexible and non-constant, the Multi-Rate model adapts better to the biological origin of the system.

Motor Adaptation | Short Term Motor Learning | Motor State Modelling in Cerebellum | Computational Modelling of Error and Feedback in Motor Adaption

Behavioural analysis of human beings and animals show adaptation of motor functions under varying circumstances (2). Savings refers to faster re-learning a task after a prior learning of that task has occurred; even if we unlearn the prior learning or let is washed out (possibly by letting a sufficient time to pass between learning sessions). The unlearning block must have enough trials so the net motor output reaches zero; and not too many trials so the net motor output changes to negative values.

Our physiological understanding of the brain indicates that motor learning and adaptation involve multiple neural processes operating at different rates and with different retention capabilities (3). The idea is that the brain utilizes distinct neural systems or states to handle motor adaptation in a more nuanced manner.

The previously presented models, such as the Single-State model, fail to adequately capture the complex dynamics of motor adaptation and learning. These models assume a single-time constant adaptation process, which limits their ability to account for various experimental observations. For example, they struggle to explain phenomena like anterograde interfer-

ence (where prior learning affects subsequent learning), rapid de-adaptation, and rapid downscaling (4). These models also face challenges in predicting spontaneous recovery or adaptation rebound when error feedback is clamped at zero after an adaptation-extinction training episode (5). In contrast, the multi-rate system proposed in this article addresses these limitations by incorporating two distinct neural states or processes. One state responds weakly to error but retains information well, while the other state responds strongly but has poor retention. This dual-state system provides a more comprehensive framework that can account for the observed phenomena in motor adaptation, including saving and washout

Significance Statement

There are several scenarios in which an animal or a human can be trained to perform a certain task requiring motor functions. Like moving your hand to grasp something. The cribellum is a part of the brain that works as the main I/O structure for motor commands. It is evident that the cerebellum cancels disturbances in the environment. It means that our brain tends to normalize every process to a baseline depending on the environment. For example, consider a scenario in which you want to shoot a gun but a forcefield is present (like gravity), therefore you have to adjust your aiming and your hand movement to cancel that force which after many trainings becomes the baseline of the performing task. When the force is removed (or is presented in the opposite direction i.e imagine shooting in a zero-gravity space), it would take some time and practising in order to again hit the target. Another scenario is that you may lose your excellence in a task if you don't perform it for a long time i.e. you forget it! When you start doing that task again, it would be much faster and easier to become skilled. All this learning, forgetting and re-learning done by our brain, can be modelled with equations. In this article we present a computational model that can account for all of the scenarios observed in lab experiments and we simulate them and compare them with reality (and also other models). Understanding the functions of the brain in a mathematical manner, helps us translate the language of the brain to something we can actually understand, and the more we understand, the better we become at manipulating it, healing it, improving it and we can push further the physical limitations of a 3-dimensional body.

of prior learning, as well as the ability to predict spontaneous recovery.

A. Defining Some of The Observed Behavioural Phenomena.

In order to understand the motivation behind deriving a Multi-Rate model (presented by A. Ghazizadeh, R. Shadmehr and M. Smith in their Interacting Adaptive Processes with Different Timescales Underlie Short-Term Motor Learning paper (1)), it is required to gain some knowledge about these phenomena which have been proved to exist in the ways that brain functions.

A.1. Adaptation. Adaptation is commonly understood as the process through which the nervous system acquires the ability to anticipate and counteract the impact of a new environment, thereby restoring movements to their baseline (unaffected) state. However, an alternative perspective suggests that adaptation is not primarily geared towards cancellation, but rather towards optimizing performance within the given environment (6).

A.2. Motor Adaptation. By practising in a new environment, we develop internal models that anticipate the sensory outcomes of motor commands. Through optimization that's motivated by rewards, we leverage these models to explore movement strategies that reduce implicit motor expenses and maximize rewards (6).

A.3. Savings. The phenomenon in which people show faster relearning of a previously forgotten memory. This has posed a challenge for learning models that rely solely on error-based processes in the motor learning domain. However, through a series of experiments, it has been shown that savings is indicative of enhanced action selection skills. Specifically, participants are better able to choose an appropriate targeting strategy when faced with a previously encountered disturbance. (7)

A.4. Anterograde interference. Suppose we have two motor tasks, A and B. We consider the scenario in which a subject initially learns task A, then after a short period of time she begins learning task B. If initially learning task A causes interference with learning and remembering task B, we say that Anterograde Interference has occurred. Previous studies show that this happens only if these two conditions are present:

1. Learning sessions for tasks A and B happen in close temporal proximity. In other words, the interference does not occur if a sufficiently long time period elapses between the two learning sessions (8, 9). (Temporally graded phenomenon.)

2. In order to observe greater interference effects, the task A and B have to be similar in which context similarity is defined as the amount of overlap between learning-specific neural networks (10).

B. Biological Plausibility.

What inspired designing a Multi-Rate model to explain the observed patterns of motor adaptation behaviour, is the physiology of the brain. Understanding the structure of the cerebellum sheds a light on why this model could fit this biological system.

The cerebellar nuclei (CN), is the main output structures of the cerebellum. It is now clear that the cerebellum controls
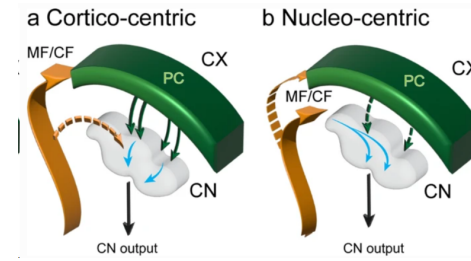

Fig. 1. The cerebellar circuitry is traditionally described as cortico-centric, with afferent inputs terminating in the cortex and passing through Purkinje cells to the cerebellar nuclei (Panel a). However, the nucleo-centric perspective suggests that the primary pathway is for afferents to synapse in the nuclei, where efferents originate, and for a complementary inhibitory signal to be generated in the cortex and sent to the nuclei via the corticonuclear pathway. (Panel b) Arrows do not represent anatomical size or signal strength, but rather relative importance of information flow. Blue arrows indicate information passing through CN circuits without reference to cell types. Figure and caption taken from (13)
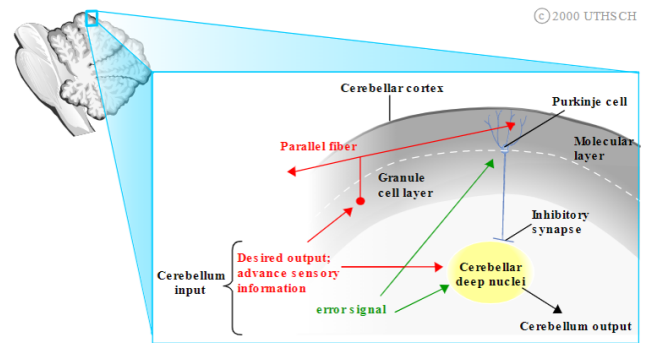

Fig. 2. The two different paths for motor state and errors in the cerebellum. Figure taken from (14).

both the memory processes necessary for associative learning and the adaptation of motor functions (11).

The cerebellar cortical dynamics are influenced by a rich sensory and motor reality that is also accessible to the CN. Meaning that CN has the ability to encode various behavioural trajectories (12). Figure 1 shows two strategic perspective of the cerebellum proposed by J.M. Kebschull (13). They suggest that than even though there is no qualitative difference between models A and B, viewing the cerebellar system from a nucleocentric perspective will reveal novel insights into the mechanisms underlying its organization and development as well as computational function. The fact that motor and error information arrive simultaneously in CN and Cerebellar cortex (shown in figure 2), justifies the idea of having a two-state model in which each state has its own learning rate. The previously presented model by Kojima Y. (5), in which states learning happens in different directions, are unable to describe anterograde interference, rapid unlearning, and rapid down scaling.

1. Results

(1) Single State Model :

$$x(n+1) = A \cdot x(n) + B \cdot e(n)$$
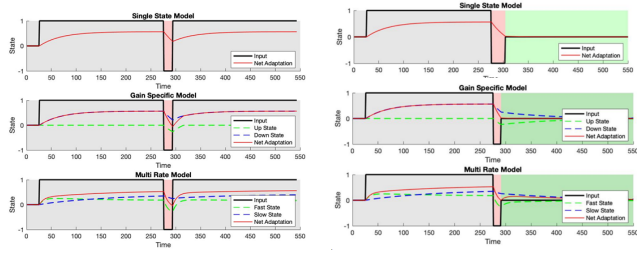$$B_f > B_s, A_s > A_f$$

Fig. 3. The output of each model comparing the speed of increasing for each models in learning and re-learning sessions. The results are analogous to what is originally presented in (1). Although these model have same trends in plots but there are significant differences, the most important one is speed of increasing in re-learning trials, in Multi rate models, this speed is more than two other models, and in Gain specific model is more than the single-state model. And in single-state model, this speed is approximately equal to the speed of increase in learning section, so this is one of the issues of this model. As we said, the speed of increase in re-learning part must be more than speed of increase in the learning part (1), and Gain Specific model and Multi-rate model have this attribute.
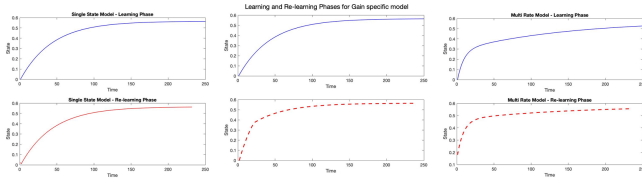

Fig. 4. Learning and re-learning for single state (Left), Gain-Specific (Middle), and Multi-Rate (Right) model

(2) Two State, Gain - Specific Model :

$$x_1(n+1) = \min\left(0, [A \cdot x_1(n) + B \cdot e(n)]\right)$$
$$x_2(n+1) = \max\left(0, [A \cdot x_2(n) + B \cdot e(n)]\right)$$
$$B_f > B_s, A_s > A_f$$
$$x = x_1 + x_2$$

(3) Two State, Gain - Independent, Multi - Rate Model :

$$x_1(n+1) = A_f \cdot x_1(n) + B_f \cdot e(n)$$
$$x_2(n+1) = A_s \cdot x_2(n) + B_s \cdot e(n)$$
$$B_f > B_s, A_s > A_f x = x_1 + x_2$$

$x(n)$: Net motor output on trial n, x_1, x_2 : Internal states that contribute to the net motor output, $e(n)$: Error on trial n, B : Learning rate, A : Retension factor.

Initially we set the variable like the article: $A = 0.99, B = 0.013, A_f = 0.92, A_s = 0.996, B_f = 0.03, B_s = 0.004$. In this part, we have four major sections, first null trials, second adaptation trials, third de-adaptation trials, and re-adaptation trials, and the length of each section is $25, 250, 18$, and 250 trials, respectively, not the length of de-adaptation trials, can be changed for each model, because at the end of de-adaptation, we want to go to zero value. You can see the plot of each model in Figure **??**, and as you see, the models results have the same trend in general. They start from zero and, with a concave curve, go to approximately 0.5, then we go to de-adaptation trials and it decreases to zero, and in this part, the speed of converging to zero is very different for these models, and finally it increases.
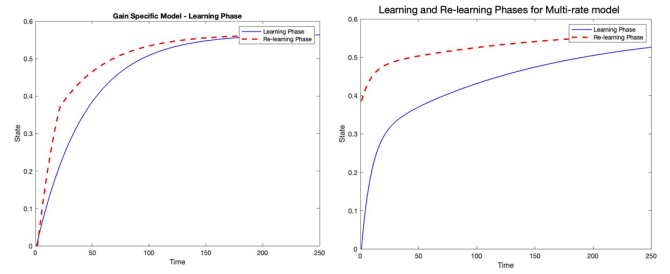

Fig. 5. We defined a parameter for measured how is good our speed in re-learning vs learning section, and it calculates as integral of fenced area between learning and re-learning curve, and in Multi this area is larger than other models and in Gain model larger than Single model. The parameter can shows how our re-learning process is better and faster than learning process, and result shown the Multi models has largest area and fastest speed Compared with other models, and single model has slowest speed Compared with other models.
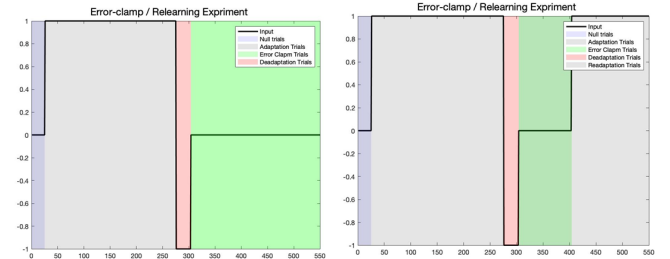

Fig. 6. By examining the different learning models and observing their behaviour in different experimental paradigms, we can gain a better understanding of the mechanisms of motor learning and the role of error-feedback in this process.Here is the results of the error clamp with a specific input structure (left), and error clamp / re-learning with washout trials (right)

A. Error Clamp. The error clamp technique was employed to further test the models' behaviours under zero-error conditions. In this paradigm, errors, which are the difference between the motor output and the environment state, are held constant at zero after the unlearning phase. This experimental approach allows for the observation of inherent changes in motor output in the absence of error feedback. The gain-specific model under these conditions predicts that the motor output will remain zero. However, the multi-rate model forecasts a spontaneous recovery or a rebound effect. The motor output briefly rebounds back towards the initial learning block before eventually settling down at zero.

A.1. Error Clamp / Re-learning Experiment. The error clamp/re-learning experiments serve to investigate the models' behaviour when an error-clamp block is followed by a relearning block. The findings from these experiments proved insightful for both the gain-specific and multi-rate models. The multi-rate model, in particular, predicts an immediate jump in performance at the beginning of the relearning block following the error-clamp phase due to the rebound in adaptation. The gain-specific model, however, does not predict this. These different predictions underline the utility of these simulations in better understanding motor learning and adaptation processes. (Figures 6,7)

B. Dynamic Parameters. In the study conducted by Ghazizade A., the parameters A, B, A_s, B_s, A_f, and B_f were assumed to remain constant throughout the trials. However, in
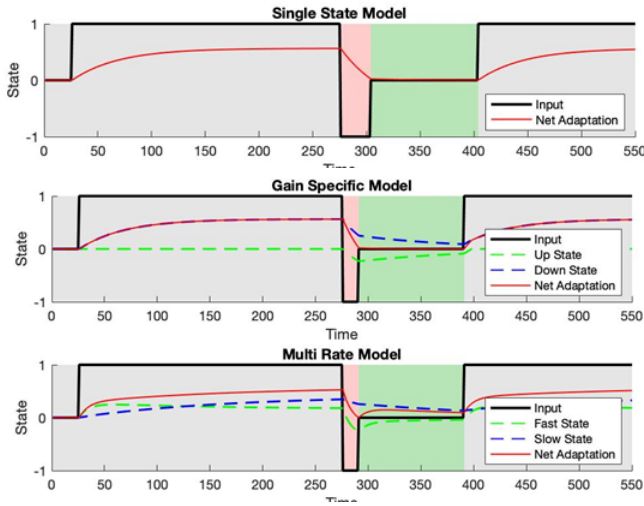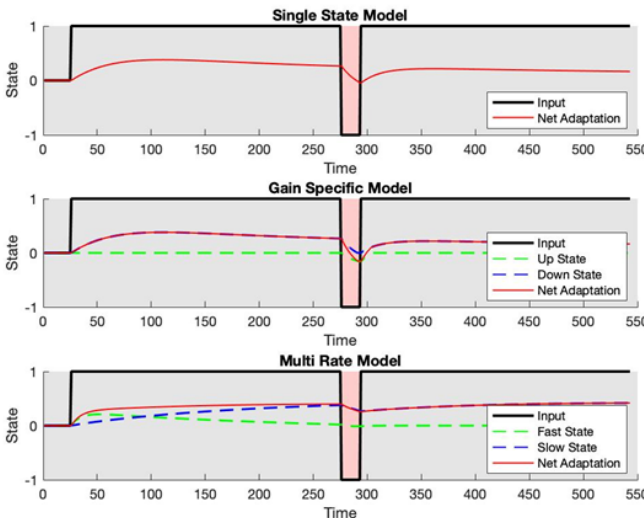
Fig. 9

Fig. 7. The final results

Fig. 8. Upon further consideration, we have recognized that using a linear decay function to decrease the parameters over trials may not accurately reflect the dynamics of motor learning. It is evident that decreasing the parameters linearly results in slower re-learning compared to the initial learning phase. Similarly, increasing the parameters linearly leads to faster re-learning compared to initial learning.
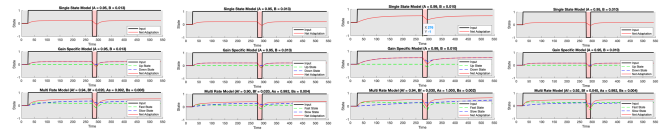
our modified approach, we introduced a linear decay function to allow these parameters to change over time. This modification was motivated by the understanding that the brain's learning system is not static but rather dynamic and capable of adapting and evolving. By incorporating a linear decay function, we acknowledge the inherent flexibility and adaptability of the brain's motor learning process. It recognizes that the learning system can undergo adjustments and variations as learning progresses. This dynamic aspect of motor learning is crucial to capturing the brain's ability to respond and adapt to changing environmental conditions. By allowing the parameters to decay linearly, we simulate the brain's potential to adjust its learning rate and retention factor over trials. This approach reflects the idea that motor learning is not a fixed process but rather one that is influenced by various factors and can exhibit variability over time. Considering the dynamic nature of the brain's learning system provides a more realistic representation of motor learning. It enables us to explore how the changing parameter values influence the learning process and ultimately shape the motor responses observed in the models (Figure 8).

To address this limitation, we propose using an alternative function that allows for a more realistic representation of the motor learning process. This function should capture the fact that re-learning can occur at a different rate compared to initial learning, depending on the specific parameters involved. By employing a non-linear function, we can better capture the complexities of the brain's learning system and the variability in re-learning speed. This function can be tailored to the specific parameters (A, B, As, Bs, Af, and Bf) and their influence on the motor learning process. Using a non-linear function enables us to explore the intricate relationship between the changing parameters and the speed of re-learning. By defining a suitable function, we can account for the nuances and intricacies of motor learning, providing a more accurate representation of how the brain adjusts its learning strategies over time. This approach acknowledges the inherent variability in the brain's learning process and avoids the oversimplification that a linear decay function may introduce. It allows us to investigate the relationship between parameter adjustments and re-learning speed more comprehensively, providing insights into the underlying mechanisms of motor learning and the dynamics of the learning system.

Another approach that we can use is set the parameters as a dynamic variable that changes; by using this approach in another word we set different range of parameters to compare plots (Figure 9).

Therefore setting the parameter is very important, and this is the reason that we cannot set parameters whatever we want, and we must change the parameters in order of article parameters.
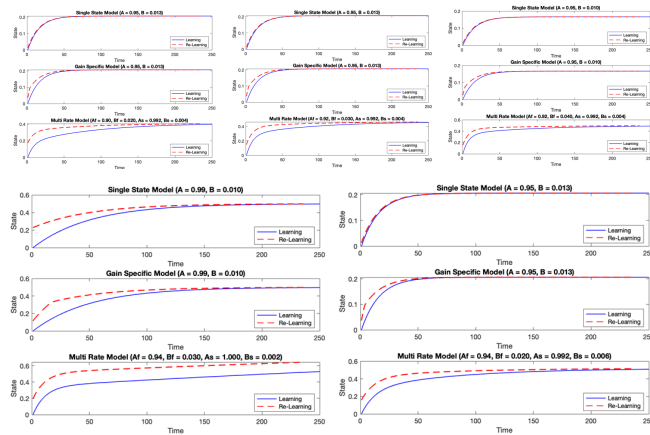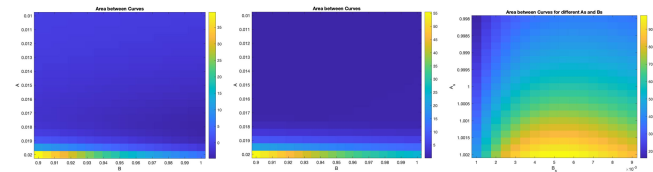
Fig. 12. Heat Map of Single-State (left), Gain-Specific (middle), and Multi-Rate model. In Multi-Rate model, we have 4 parameters, so in first step we change A_s and B_s parameters and show the contour plot of area between curves. The Multi-Rate model performs much better than other models in the parameter range, it does not go to outlier value by some parameters, but those two models go to very large and non-disabled value. Also we calculate area between learning and re-learning curve for different A, B, A_s, B_s, A_f and B_f parameters
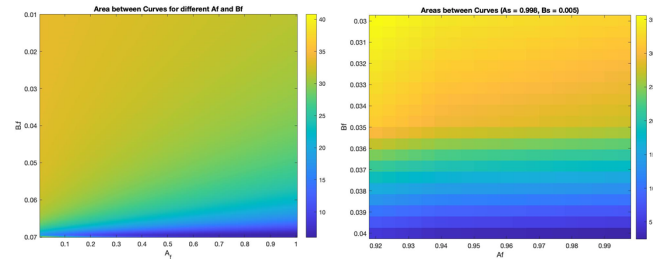

Fig. 10. learning and re-learning curves for different models parameter

Fig. 13. Changes in A_f and B_f

Another achieved result in this section is presented in Figure 12. as you can when we set some parameter, the Single and Gain models approach irrational values but the Multirate model does not diverge to enormous values and shows the privilege of the multi-rate model compared to other ones.

C. Adding Noise. In the context of motor learning, the influence of noise on the models can provide insights into the robustness and stability of the learning process.we suggest considering two types of noise: pink noise and Gaussian noise.

C.1. Pink Noise. Pink noise is a type of noise that occurs in various biological phenomena, including motor systems. It is characterized by a frequency spectrum where the power density decreases as the frequency increases. In the context of motor learning, the introduction of pink noise can simulate the inherent variability and fluctuations observed in biological systems.

By incorporating pink noise into the models, we explore how the presence of this noise affects the learning process (Figure 14). It examines whether the models can still accurately capture motor adaptation and re-learning in the presence of such noise. The analysis helps assess the robustness and resilience of the models against natural variations in the motor system.

C.2. Gaussian Noise. Gaussian noise, also known as white noise, is a type of noise that has equal power at all frequencies. It is commonly used to represent random fluctuations or perturbations in a system. In the context of motor learning, Gaussian noise can simulate external disturbances or measurement errors that can affect the motor output.

We investigate the impact of Gaussian noise(by adding Gaussian noise between 0 to 0.001) on the models by introducing random perturbations to the motor output (Figure 15). This
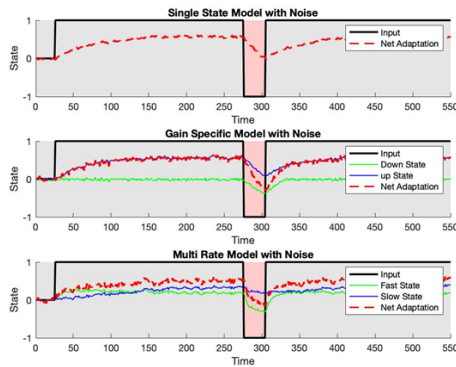

Fig. 11. In some cases like this, we set the parameter to random value and it converge to very big number

Fig. 14. As you can see, we have a fluctuation in net adaptation and other component Also, in Multi-model, the Fast state and Slow state are noisy and pink noise has a strong effect on these component we can conclude that the Multi-model is sensible to pink noise more than other models
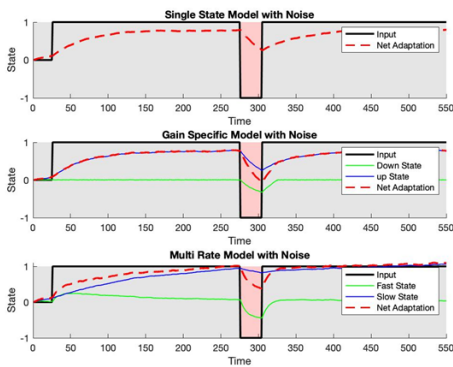

Fig. 15. In the Gaussian noise we have fluctuation in output result but it less than pink noise, and we have same trend in two type of noise, as you see in the Multi-rate model, net adaptation and Fast and Slow states are very different compare to output without noise, so in this part like in Pink noise part, we can conclude that the noise has strong effect on Multi-rate model although the pink and Gaussian noise change the Single state and Gain specific models output but they changes not remarkable as well as Muli-rate change.

allows for the evaluation of how the models respond to noisy input and how well they can adapt to and compensate for such disturbances. The analysis provides insights into the models' ability to filter out noise and maintain accurate motor performance.

Additionally, you can see the plots for the area between curves of learning and re-learning. we calculated this trapped area, and compared it to the result without noise.(Figures 16, 17, and 18)

2. Materials and Methods

To demonstrate the differences between the three motor adaptation models (Single-State, Gain-Specific, and Multi-Rate), we will design a task that incorporates prior learning, unlearning, and re-learning blocks. We will also add a washout block after unlearning to compare the results. Additionally, we will vary the decay factor and learning rate to assess the generalization of the results. Lastly, we will explore the use of a dynamic learning factor and decay factor, as well as compare the results when the two-state multi-rate model is replaced with cascade formation.

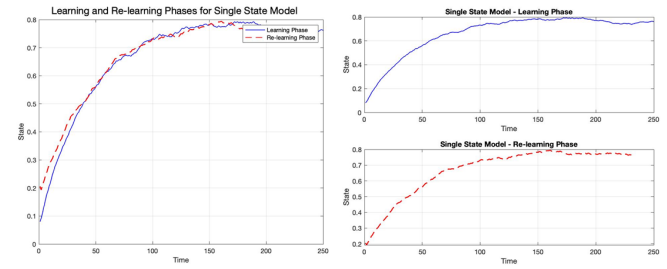Some parameters approach infinity, and we bring some of

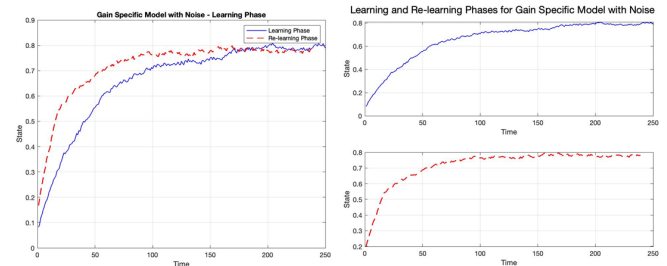**Fig. 16.** Difference of the trapped area between curves in Single-State Model

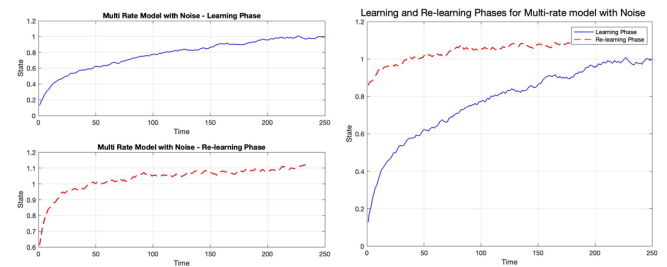**Fig. 17.** Difference of the trapped area between curves in Gain-Specific Model

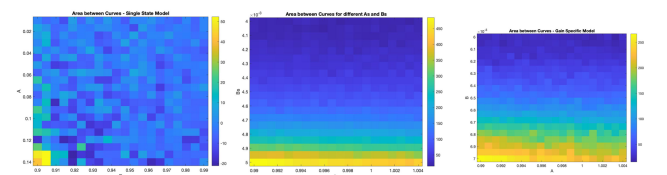**Fig. 18.** Difference of the trapped area between curves in Multi-Rate Model

Fig. 19. By changing parameters of each model we calculate the trapped area and plot the result as contour plot like in previous part (without noise part) We showed the result for Single state, Gain specific and Multi-Rate respectively.
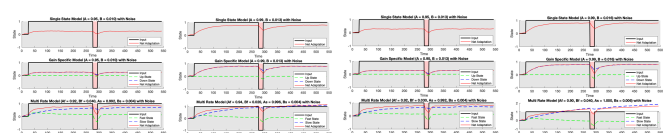

Fig. 20. The learning and unlearning and re-learning curves for some random parameters for each model. As you can see, Gain and Single models are more resistant to noise but the Multi-Rate model is very sensitive to noise.
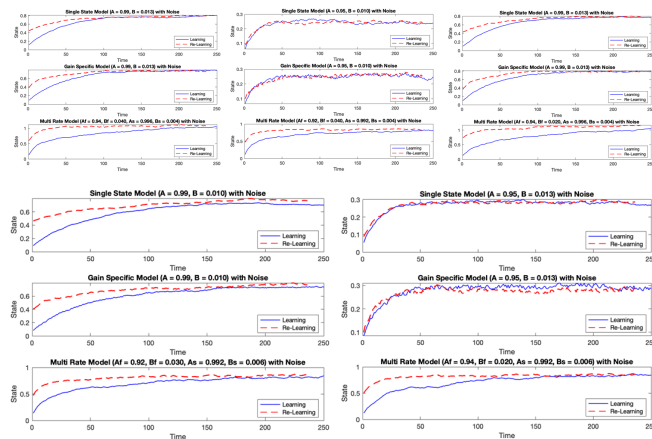
Fig. 21. The learning and re-learning curves for some random parameters for each model
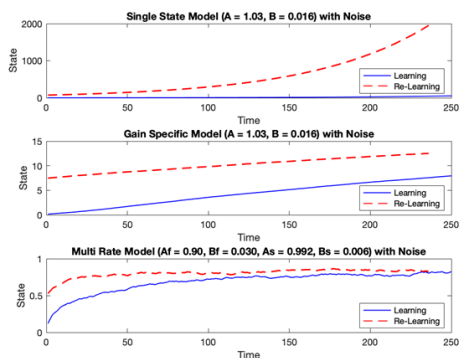

Fig. 22. Examples of bad parameters that cause outlier values in Single and Gain model

specific model is a two-state model with each state linked to the direction of adaptation. Both up and down states contribute to relearning which makes relearning faster compared to initial learning. The third model, the multi-rate model, also incorporates two states. However, the states here are not direction-specific but rate-specific. This model operates on different timescales, one state responds rapidly to errors (fast rate), while the other responds slowly (slow rate). At the start of relearning, the slow state is already biased towards relearning, thus relearning is faster than initial learning.

B. Simulations.

B.1. Task Design.

- Set up a motor adaptation task, such as reaching movements or eye saccades, where participants need to adapt their motor commands to compensate for external disturbances.

- Divide the task into three blocks: prior learning, unlearning, and re-learning.

- In the prior learning block, participants will gradually learn the correct motor responses through repeated trials.

- In the unlearning block, participants will be exposed to a different condition or disturbance that requires them to unlearn the previously acquired motor responses.

- In the re-learning block, participants will be reintroduced to the initial learning conditions to assess the speed and extent of re-learning.

B.2. Adding a Washout Block.

- After the unlearning block, introduce a washout block where participants perform trials without any feedback or disturbance.

- Compare the motor responses during the washout block across the three models to examine their ability to retain prior learning and the speed of re-adaptation.

B.3. Varying Decay Factor and Learning Rate.

- Modify the decay factor and learning rate in each model and repeat the prior learning, unlearning, and re-learning tasks.

- Compare the results across different parameter values to investigate the influence of these factors on the speed and extent of adaptation and re-learning.

- Assess if changing these parameters affects the models' ability to generalize the results and reproduce the observed phenomena, such as savings and washout.

B.4. Dynamic Learning Factor and Decay Factor.

- Implement a dynamic learning factor and decay factor in the models, where these factors change over time or in response to certain conditions.

- Repeat the task and compare the results with the static parameter values to evaluate the impact of dynamic factors on motor adaptation and re-learning.

them. As you remember, we have some very different point in the contour plot in the previous part; these points are these parameters that converge to very big value, and this show why choosing parameters is very important; we set the parameters of each model in according to values presented by Ghazizadeh A. Also, we have the same result as the previous part(without noise), Multi-rate mode is more sensitive to noise compared to other models, but in learning and re-learning curves for some parameters, these two models(Single and Gain) converge to large and non-sensible numbers but Multi-rate model does not go to this large number and in this concept, multi-rate model is extremely better than other models, in another word multi-rate model with all range of parameters working and does not have outlier value but single and Gain model can go to nonsense value.

A. Introduction of the Models. The research explored the nature of motor learning through the simulation of three distinct models: a single-state model, a gain-specific model, and a multi-rate model. Each model illustrates how motor output can adjust in response to the current motor state and errors observed during trial runs. In the single-state model, the motor output at any given trial is a function of the previous motor state and the error encountered during that trial. This model has a uniform time-constant and lacks the capacity to exhibit motor output patterns that show savings. The gain-

B.5. Cascade Formation Model.

- Replace the two-state multi-rate model with a cascade formation model, where the learning and retention processes occur sequentially or in a cascading manner.

- Repeat the task and compare the results obtained from the cascade formation model with the previous models.

- Analyse the differences in motor adaptation, savings, washout, and re-learning to assess the strengths and limitations of the cascade formation model.

By systematically comparing the results obtained from different models and manipulating various parameters, we can elucidate the distinctive features and capabilities of each model in capturing motor adaptation, savings, washout, and re-learning phenomena. This comprehensive analysis will provide insights into the underlying mechanisms of motor learning and help understand the implications of different modelling approaches.

3. Discussion

We added the effect of Pink Noise which is a common disturbance observed in biological processes (15) to these models, and it seems that the Gain-Specific model shows more stable performance than the Multi-Rate model.

It can be challenging to reconcile the concept of strict competition with other behavioural evidence. Specifically, research has demonstrated that motor tasks A and B can both be learned and retained when they are practised in diverse contexts (16) even if their learning involves common motor cortical areas (17). Moreover, acquiring differing motor tasks in an interleaved manner in the same context facilitates their long-term storage, a well-documented effect referred to as contextual interference. (18). Thus, there is the possibility that a mechanism other that competing memories is responsible for the Anterograde Interference. This approach assumes that the baseline movements are the optimal movements in all conditions, but this has been proven to be false. For instance, in cases where a spring-like force alters the path of least resistance between two points to a curved path rather than a straight line, individuals adapt to this new dynamic by reaching along the curved path (19). Taking into account this fact, can help improve the model towards having a dynamic capacity for converging toward the optimal path in the presence of a forcefield and demonstrate more stability when noise is present.

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