Optimization of Structural Complexity in Motor Adaptation Expressed by a Simple Multi-Rate Learning Model

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In the past 30 years, the study of human motor control has seen the discovery of several motor adaptation phenomena, or unique ways in which the motor system responds to a particular task it is given to learn. As each one of these phenomena was observed, researchers proposed mechanisms that could possibly explain what they saw. As the number of phenomena increased, the number of these explanations also began to increase, and most of them had no explicit connection with the others. As more and more phenomena are discovered, it is straightforward to predict that more independent explanations will be provided. Imagine, however, what would be required of the brain if each and every task given to the motor system was processed in a different way. Given the exceedingly large number of possible inputs, the motor system would have to have an enormous "look-up" table that it could reference each time it decided to process a task. The inefficiency of such a system is clear, and strongly suggests that there exists a better, and perhaps optimal, solution to the question at hand.

Savings is the ability of prior learning to speed up subsequent relearning even after behavioral manifestations of the prior learning have been removed.[i] The researchers who discovered this phenomenon proposed that a two-state, gain-specific computational model could explain this behavior. The same researchers observed *spontaneous recovery*, or the re-appearance of learning after a period of null learning through the removal of relevant error, but were unable to explain this recovery.[i] *Rapid unlearning* and *rapid downscaling*, or the observations that fully or partially unlearning a motor adaptation can be faster than the initial learning of the adaptation, are possibly a result of difference in time constants in activation and deactivation of motor processing units in the brain.[ii] *Anterograde interference (AI)*, or the ability of a previously learned motor adaptation (task A) to reduce the rate of subsequently learning a different (and usually opposite) motor adaptation (task B), is posited to be caused by lag time in switching neural internal models for task A to task B.[iii] These different explanations of phenomena lead down a path that espouses the inefficient look-up table theory. However, a more tractable solution would be if a single, unifying model could handle all of the aforementioned phenomena. In fact, if complexity of system structure was a parameter of interest, then one could argue that such a proposed unifying model could be the optimal solution, when optimizing around this parameter.

Figure A: Anterograde Interference Simulation Adaptation Curve

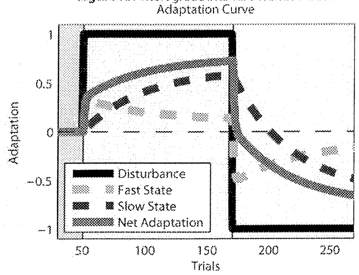
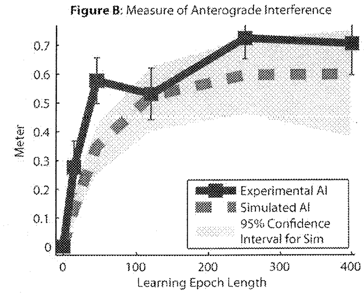


Figure B: Measure of Anterograde Interference



It has recently been shown that a two-state, multi-rate learning model can largely capture every one of these motor adaptation phenomena.[iv] This model has a fast process and a slow process, where the fast process learns quickly, but forgets quickly, and the slow system learns slowly, but has a high retention rate. The interaction of these two processes provides a unifying computational model that not only explains the cause of savings, spontaneous recovery, rapid unlearning and downscaling, and AI, but can also be used to make predictions about each of these phenomenon. Specifically, while discussing AI (see **Figure A**), the slow process lags behind the fast process when the motor system is required to learn task B after having learned task A. This residual contribution of the slow process is precisely what causes the reduced learning rate of task B observed in AI. With this understanding, the model makes the following predictions – **1)** significant AI exists, **2)** as the time spent learning task A is increased (or in other words, as the slow system learning is raised), the more AI will occur, and **3)** after a certain duration of time of learning task A, AI will level off or asymptote. **Figure B** shows the simulated and experimental AI results, once AI is characterized with a metric based on learning curves similar to the one shown in Figure A. The correspondence between the predicted and actual metrics is quite remarkable, and is not restricted just to this phenomenon – the previously unexplained spontaneous recovery has also been experimentally shown to have exceptionally good correspondence with behavior predicted by this model[iv], and the other phenomena only lack verification.

Finding a unifying theory has often been a goal of scientists, as seen in the attempts to bring together the fundamental forces of physics. This sense is also expressed in motor control, when given the two options of a massive neural lookup table and a simple two-state, multi-rate learning model to explain motor adaptation. When optimizing around the parameter of structural complexity of motor adaptation neural processing, the multi-rate model is clearly the more optimal solution, and could be, in fact, the optimal solution.

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