Patterns of Anterograde Interference in Reaching Arm Movements Explained by a Multi-Rate Learning Model

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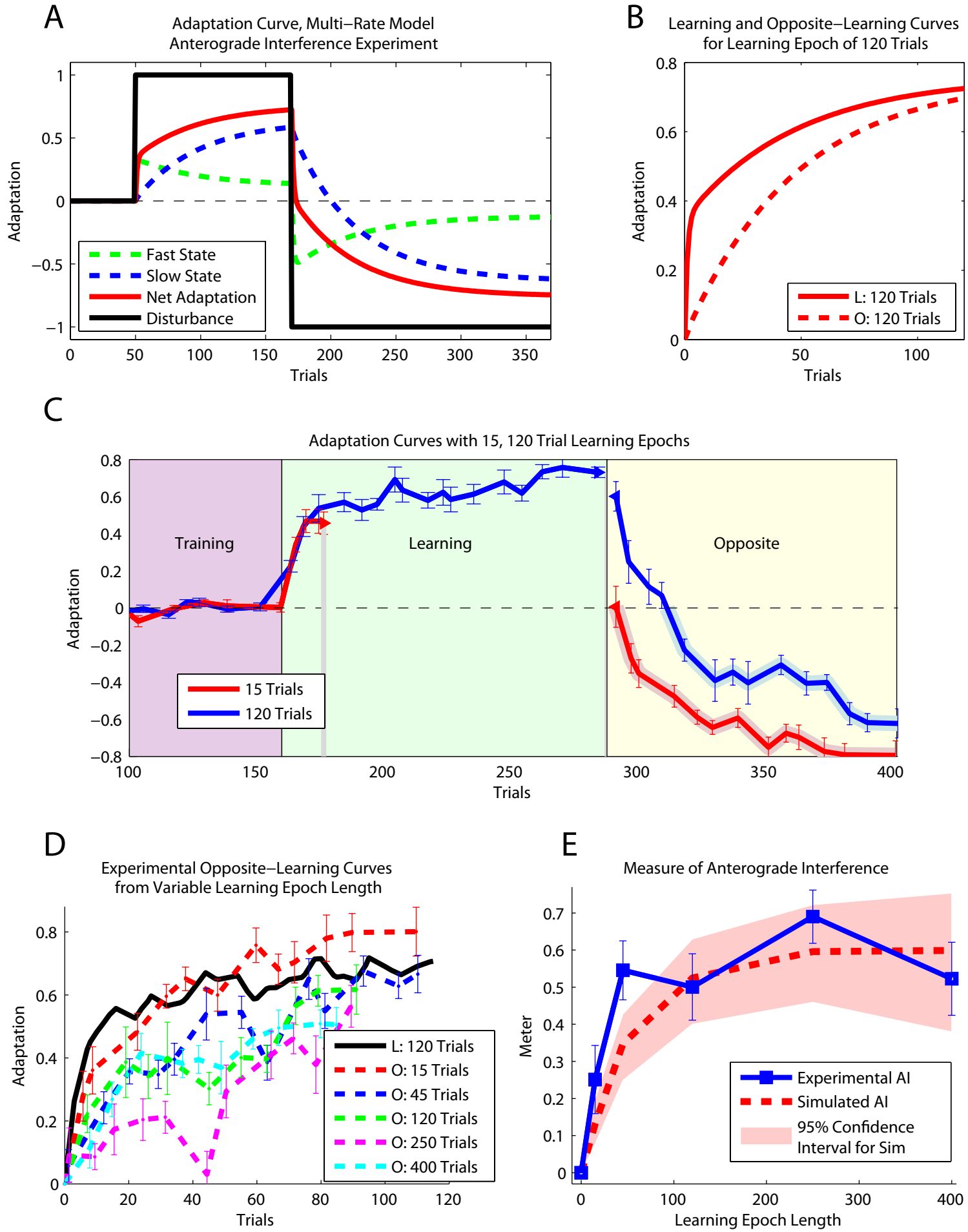
The human motor system is a complex network of sensors, neural processing elements, and actuators that combine to plan movements, to execute those plans, and to modify how those motor plans are carried out. We have recently shown that a simple learning model with two distinct, but interacting adaptive processes can largely capture several key properties of motor adaptation traditionally considered to be separate phenomena. These properties include savings, the washout of savings, rapid unlearning, rapid downscaling, spontaneous recovery, and anterograde interference. One of the most important of these properties is anterograde interference (AI), which is the ability of a previously learned motor adaptation to reduce the rate of subsequently learning a different (usually the opposite) motor adaptation. Here, we closely examine the formation of the motor system's capacity for AI by studying how the duration of the initial (interfering) learning epoch influences the amount of AI.

We previously found that two distinct learning processes underlie short-term motor adaptation, and we hypothesize from this modeling work that the amount of AI increases with the build up of the slower of these learning systems, rather than with the faster learning system or the net (total) amount learned. Specifically, our two-state learning model predicts (1) that significant AI will occur, (2) that the amount of AI will increase if the length of the initial learning period is increased, and (3) that beyond 100-200 initial learning trials the amount of AI will level off.

Our experimental paradigm consisted of having subjects grip a manipulandum arm and make straight arm-reaching movements in several blocks of trials, each ranging from 5 to 10 minutes in duration. Our subjects, after training for 150 null-field baseline trials, were exposed to an initial learning period, consisting of a velocity-dependent clockwise curl force-field, for a variable number of trials - either 15, 45, 120, 250, or 400 trials. The opposite force field (a counterclockwise curl field) was then applied for approximately 120 trials. Interspersed throughout the experiment were force-channel trials during which lateral motion errors were clamped near zero (errors were held to less than a millimeter), effectively removing online error feedback and allowing clear assessment of feedforward adaptive changes in lateral force profiles related to the adaptation task. These lateral force profiles were regressed onto the ideal force profiles desired for perfect force-field compensation to determine the coefficients of the best-fit straight line. The regression coefficients we obtained were used as a measure of the amount of adaptation. Figure A shows a simulated adaptation curve showing the effect of AI plotted as a solid red line – the fast & slow processes hypothesized to underlie the net learning curve are shown as dashed green & blue lines, respectively. At the point at which the adaptation curve crosses zero during the opposite-learning epoch, the contributions of the slow and fast states are equal and opposite. It is this residual slow contribution that leads to the phenomenon of AI. After the zero-crossing, as the adaptation curve dips below zero, the slow process remains above for some period, holding back learning of the oppositely-directed disturbance. Figure B shows a direct comparison of the learning and opposite-learning curves for this simulation with 120 learning trials. In order to provide a fair basis for comparison between the rates of initial and secondary learning, the zero-crossing points pre- and post-learning-epoch were used as the starting points of the two curves. Aligning the various curves at their zero-crossings allows for a fair comparison of the learning curves in each experiment because these curves start from initial points with the same motor error and the same overall learning state. Two experimental adaptation curves (15 and 120 trials) are displayed in Figure C to qualitatively show the effect of the learning epoch length. Note the slightly steeper slope of the 15 trial group immediately after the zero-crossing (the highlighted portion), as compared to the 120 trial group. This distinction, as well as the differences between the other groups, becomes clearer in Figure D, which plots the experimentally-obtained opposite-learning curves for all groups aligned at zero-crossing.

We ran simulations using sets of model parameters that were obtained in a previous study by bootstrapping data from an entirely different learning paradigm (Smith et al 2006). These simulations predict what the opposite-learning curves of the different groups would look like if produced by a two-state learning system. Depictions of these simulations (which display 95% confidence intervals for model prediction) show that the model predicts that amount of AI would initially increase with the duration of the initial-learning epoch (however, the expression of AI should reach steady state beyond a 100-200 trial learning period), and that AI should be more pronounced early on in the opposite-learning curve than towards the end. In order to take advantage of this early-AI characteristic, we created a metric of AI based on the normalized amount of opposite-field learning within an early 20-trial bin (between the 5th and 25th trials after zero-crossing of the opposite-learning curves seen in Figure D). The estimates of this AI metric for experimental and simulated data in Figure E show (1) that indeed, substantial AI is occurring, (2) that as the learning epoch length increases, the amount of AI also increases, and (3) that past a certain learning period length, the amount of AI begins to level off. These findings suggest that a simple two-state learning model can explain several newly-discovered properties of AI.


A
Adaptation Curve, Multi−Rate Model
Anterograde Interference Experiment
Adaptation
Trials
Fast State
Slow State
Net Adaptation
Disturbance
B
Learning and Opposite−Learning Curves
for Learning Epoch of 120 Trials
Adaptation
Trials
L: 120 Trials
O: 120 Trials
C
Adaptation Curves with 15, 120 Trial Learning Epochs
Training
Learning
Opposite
Adaptation
Trials
15 Trials
120 Trials
D
Experimental Opposite−Learning Curves
from Variable Learning Epoch Length
Adaptation
Trials
L: 120 Trials
O: 15 Trials
O: 45 Trials
O: 120 Trials
O: 250 Trials
O: 400 Trials
E
Measure of Anterograde Interference
Meter
Learning Epoch Length
Experimental AI
Simulated AI
95% Confidence
Interval for Sim