A novel mechanism for the spacing effect: Competitive inhibition between adaptive processes can explain the increase in motor skill retention associated with prolonged inter-trial spacing.

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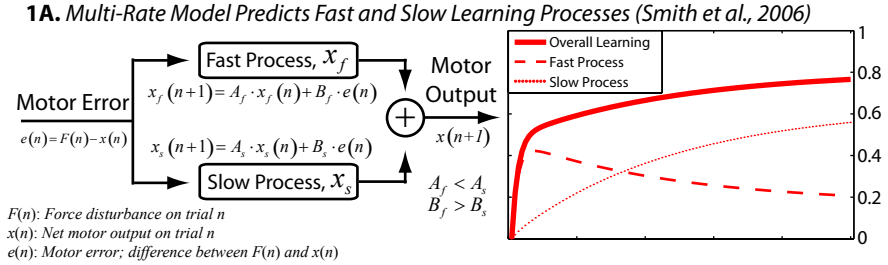
In his classic treatise on memory and retention published in 1885, Ebbinghaus showed that when learning a list of nonsense syllables, retention was better when training was spaced over several days (spaced training) than when it was concentrated into a single session (massed training). This finding - that spaced training leads to better retention than massed training - is termed the *spacing effect* and is consistently observed across a wide range of learning paradigms (Melton 1970). The spacing effect has implications for any task for which long-term retention is important, ranging from education to motor learning. Consequently, extensive research has been aimed at understanding the mechanism underlying this phenomenon (Hillary et al., 2003) because such an understanding could lead to the development of optimized training schedules. But even after a century of work, there is still no consensus as to its mechanism (Cepeda et al., 2006). Furthermore, many of the psychological theories about the spacing effect are entirely qualitative in nature, preventing them from making testable quantitative predictions. Here, we propose a novel quantitative computational model for the spacing effect in motor adaptation and provide direct experimental evidence for its mechanism.

We recently proposed a multi-rate learning model (Smith et al., 2006) that is composed of two separate, error-driven learning processes that learn in parallel with one another (Figure 1A). The "fast" process learns quickly but forgets quickly, while the "slow" process learns slowly but has better retention. The net output of this model (i.e. the sum of these two processes) represents the overall motor adaptation observed. Our recent work has revealed two properties of these learning processes that may help in understanding the spacing effect. First, although both processes contribute to initial learning, only the slow process provides a gateway to long-term retention (Joiner and Smith, 2008; see Figure 1B). Second, while both processes exhibit decay, the fast process decays rapidly as a function of time, whereas the slow process does not. Thus, these processes partition overall adaptation into temporally-labile (T-L) and temporally-stable (T-S) components. Specifically, after subjects reached asymptotic learning of a velocity-dependent force-field, exposure to various time delays ranging from 5 to 1200sec led to a decay pattern that was well-characterized by a single exponential with a time constant of about 20sec and a magnitude of 0.20 (Figure 1C). Interestingly, the multi-rate model's predicted level of the fast process at asymptote is also about 0.2. When we partitioned adaptation into T-L and T-S components by testing adaptation before and after 1min delays at 13 different points during training, we found that the learning curves for the T-L and T-S components matched the fast and slow processes, respectively ($r>0.96$ for both, Figure 1D).

How can these two properties help to explain the spacing effect? If the fast process is T-L, then longer inter-trial intervals (ITIs) will induce greater decay of this process between trials (Figure 2). This, in turn, will lead to lower overall learning, and consequently greater errors. Since both learning processes are driven by error (see Figure 1A), the slow process, which provides a gateway to long-term retention (LTR), will increase. In summary, although longer ITIs will lead to lower overall learning, the T-S slow process will be elevated, leading to higher levels of short-term retention (i.e. after 1min, STR) and LTR (here defined as after 24hrs). Note that levels of STR and LTR should be highly correlated because both are dependent on the slow process.

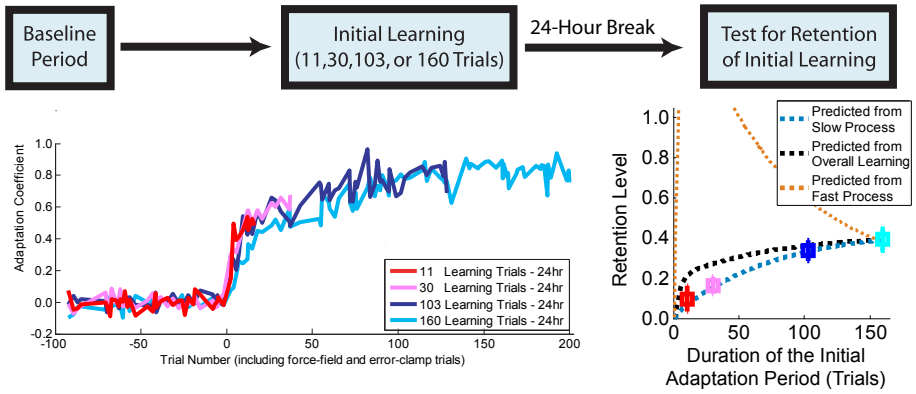
To understand where this explanation might be able to explain the spacing effect, we recruited 48 subjects to adapt to a velocity-dependent force-field while making reaching arm movements. We divided the subjects into 2 groups with ITIs of 3 and 16sec (ITI-3 and ITI-16). In addition to measuring the learning curves for these groups, we also tested (1min) STR levels at two points during the training session and (24hr) LTR levels the next day. Overall, we found patterns of learning and retention (Figure 3A) which demonstrated that although longer ITIs led to lower overall learning, they still led to greater STR and LTR ($p<0.002$, Figure 3B). In fact, the relative increases in STR and LTR associated with longer ITIs (43±10% and 50±8%, respectively) were very similar to the 40% increase predicted by the multi-rate model. When we looked more closely at the specific quantities described in Figure 2, we found that the long-ITI group displayed a significantly smaller T-L component of adaptation, indicating a reduced level of the fast process ($p<10^{-6}$, Figure 3B). This led to lower overall learning and higher errors ($p<0.002$), and remarkably to higher levels of STR ($p<0.001$ both times it was measured). Importantly, the ratio between the levels of LTR and final learning were significantly different in the short-ITI and long-ITI groups ($p<0.002$, Figure 3C). However, the ratio between the levels of LTR and STR were almost identical for the short-ITI and long-ITI groups ($p=0.68$, Figure 3C). This indicates that although final learning levels cannot account for LTR levels, STR levels can, in keeping with the idea both LTR and STR depend on the slow process. These findings reveal that two mutually-inhibitory learning processes can provide a quantitative account for the spacing effect (Figure 3D) and a computational model of their interactions can predict the magnitude of this effect.

1A. *Multi-Rate Model Predicts Fast and Slow Learning Processes (Smith et al., 2006)*

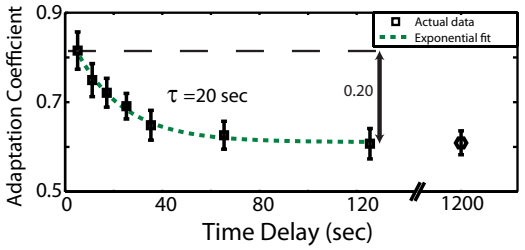


$F(n)$: *Force disturbance on trial n*
$x(n)$: *Net motor output on trial n*
$e(n)$: *Motor error; difference between $F(n)$ and $x(n)$*

1B. *Slow Learning Process Is the Gateway to Long-Term Retention (Joiner and Smith, 2008)*



1C. *Fast Process is Temporally-Labile, Slow Process is Temporally-Stable*



1D. *Temporal Stability Experiment Directly Measures Fast and Slow Process Contributions*

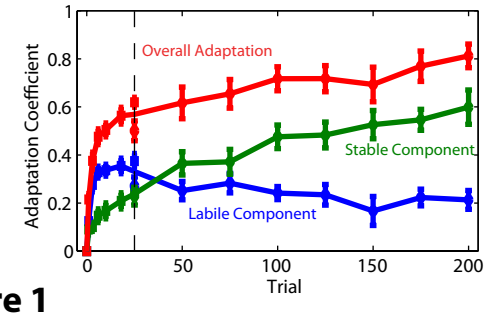


Figure 1

Figure 2 *Multi-Rate Model Can Explain The Spacing Effect*

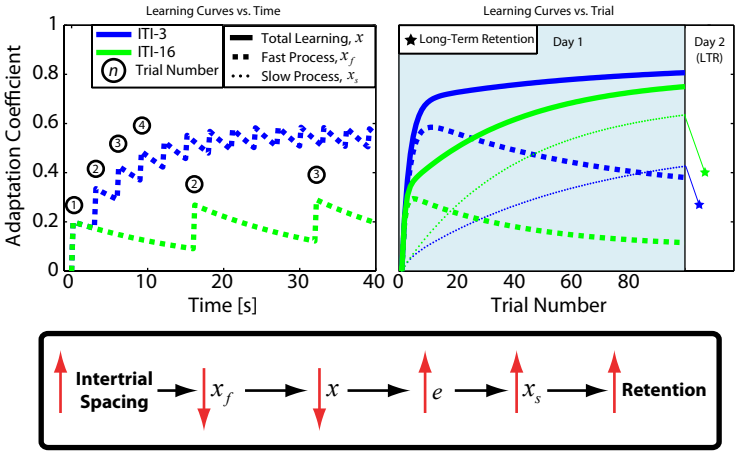
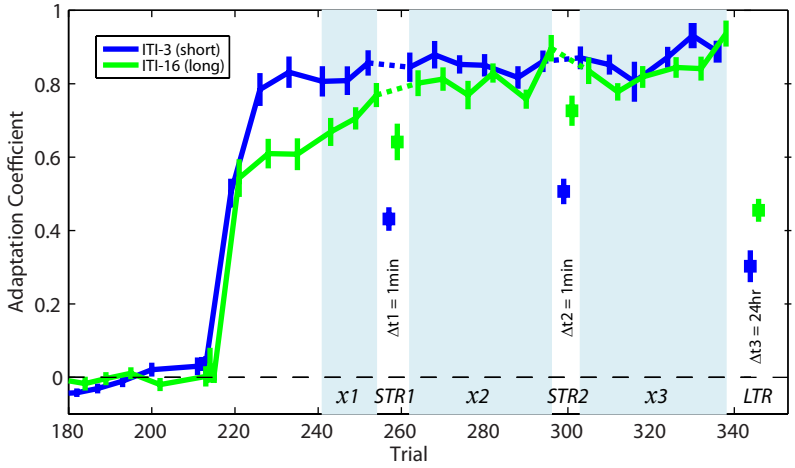
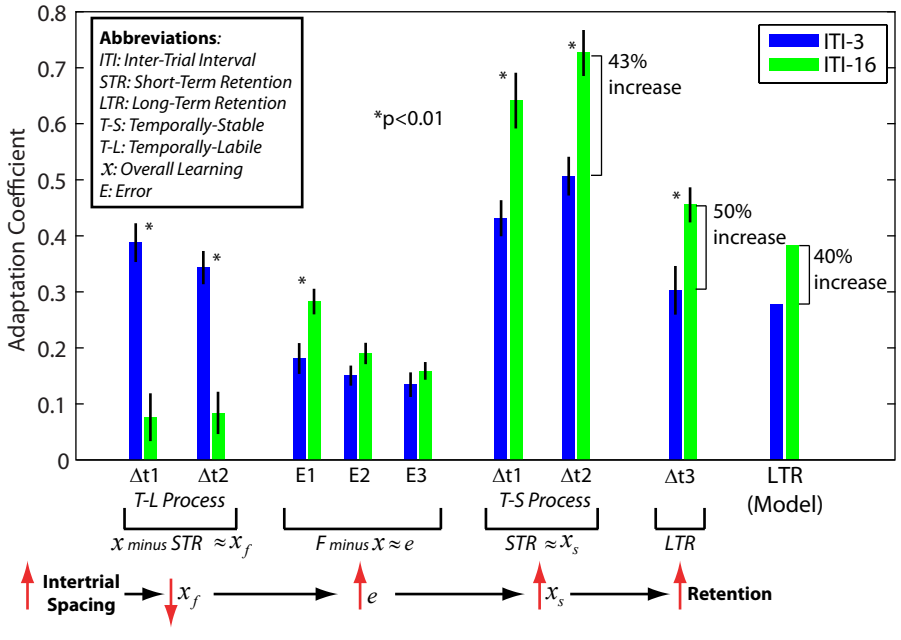


Figure 3

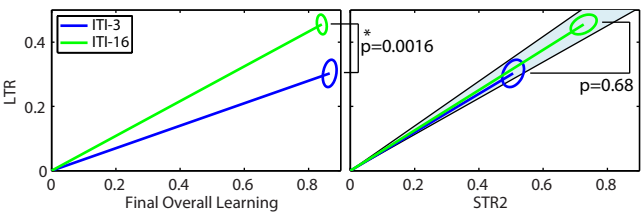
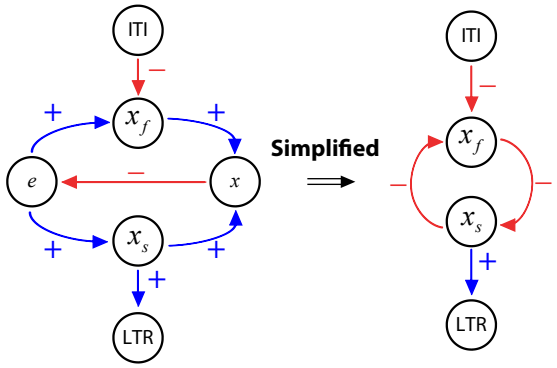
3A. *Learning Curves and Retention for Different ITI Groups*



3B. *Experimental Evidence for Multi-Rate Model in the Spacing Effect*



3C. *Slow Process Determines Both STR and LTR*



3D. *Circuit Diagrams of the Multi-Rate Learning Model*