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PRACTICE SCHEDULES, TIME SCALES AND MOTOR LEARNING

A Thesis in

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by

Adam C. King

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The thesis of Adam C. King was reviewed and approved* by the following:

Karl M. Newell
Professor of Kinesiology
Department Head of Kinesiology
Thesis Advisor

Semyon M. Slobounov
Professor of Kinesiology

David A. Rosenbaum
Distinguished Professor of Psychology

*signatures on file in Graduate School

ABSTRACT

There are multiple processes that are active both during and between practice sessions for the acquisition of a new motor skill. Distinctively separate processes of adaptation and learning can be decomposed from performance dynamics through a two time scale model. This allows for analysis of the independent effects of practice schedule distribution on these two constructs. Memory consolidation has shown improvement over time between practice sessions in certain motor tasks. This study investigated the effect of practice trial *and* practice session interval distribution on adaptive warm-up effects at the beginning of a practice session and persistent learning effects over practice sessions. The findings did not support 'off-line' enhancement from extended time between sessions; however, practice schedule manipulations modulated the adaptation process of skill acquisition.

Keywords: Practice Schedules, Time Scales, Consolidation, Learning Rate

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CHAPTER 1. INTRODUCTION

The amount of time spent in and between practice sessions of newly acquired motor skills has significant theoretical and practical implications. Obviously, a number of different kinds of behavioral changes are evident during a practice session; however, the time interval between practice sessions may prove to be just as valuable in learning. The behavioral changes are related to neurophysiological changes in the brain during periods of acquisition and periods of rest, identified as memory consolidation (Lechner, Squire, & Bryne, 1999; McGaugh, 2000). In terms of encoding, storage, consolidation and retrieval, the evolutionary time course of a new motor memory remains unclear.

The behavioral changes associated with skill acquisition through practice reflect the underlying processes of adaptation and learning. The structure of practice in the form of the degree of repetition of trials and the distribution schedule between practice sessions has a strong influence on the learning and performance of motor skills. This thesis investigates the core aspect of the practice schedule issue: namely, the effect of the time duration between both practice trials *and* practice sessions on motor learning and performance. The general finding has been that distributed practice enhances learning more than massed practice (for review see Lee & Geneveso, 1988). Recent developments in the dynamics of motor learning provide a new way to consider the effects of practice schedules based on the decomposition of the time scales of performance dynamics relative to adaptation and learning (Newell, Mayer-Kress, Hong, & Lui, 2009).

Practice Distribution

The theoretical constructs of Snoddy (1935) and Hull (1943), in addition to the original work of Ebbinghaus (1885), stimulated investigations of massed and distributed practice schedules in motor learning. Through many experiments on practice schedules, one central result has emerged: namely, that the massing of practice trials suppresses performance (Adams, 1987). However, conflicting findings have led to different views on the effects of massed practice on learning. Adams (1987) proposed that massed practice influences how well one performs, but not how well one learns, while Schmidt (1982) proposed that massed practice is a strong performance variable and a weak learning variable.

Several experiments tested the hypothesis of conditioned inhibition (Hull, 1943) or permanent work decrement (Ammons, 1947) in relation to the scheduling of practice trials and sessions. Initial work on inter-trial intervals focused on Hull's theory of reactive or conditioned inhibition. For a given conditioned stimulus, the amount of conditioned inhibition grows gradually within a practice session leading to a decrease in the level of response to the stimulus. This led to manipulations of work-rest ratios on the pursuit rotor apparatus that implemented various rest periods between trials within a single session. Bourne and Archer (1956) progressively increased the inter-trial interval for a continuous time on target task involving the pursuit rotor and showed findings supporting the reactive inhibition hypothesis. Performance decrement occurred in groups that had little rest between trials. Additionally, the amount of reactive inhibition that built up during distributed practice trials condition was significantly less when compared to trials that were repeated with no rest period. However, Bourne and Archer (1956) interpreted the findings during the initial practice session to be an inequality to learning between the groups, which can be argued against with shifting the distribution of practice trials between sessions (Denny, Frisbey, & Weaver, 1955).

The decrement in performance level under the massed trials condition may actually be a condition effect. When a shift in practice schedule distribution of trials occurred on a subsequent practice session (i.e. participants who initially performed in the massed condition get transferred to a distributed condition) participants regain a performance level indicative of participants performing entirely under the distributed trials condition (Adams & Reynolds, 1954; Denny et al., 1955). Moreover, when participants initially perform under the distributed condition and then shifted to a massed condition performance decrement becomes evident as the amount of reactive inhibition increases.

The majority of the early work of practice schedule distribution focused on either a single session or with a short rest interval between sessions. Few studies investigated the larger scale effect of distribution of trials across multiple days (Adams, 1952; Digman, 1959). When participants practiced for five days under a single constant condition (only massed or only distributed trials) performance levels eventually reached a similar level (Adams, 1952). Adams (1952) identified a warm-up decrement within both practice conditions that is marked by rapid improvement during the initials trials followed by a return to improvement rate seen in previous acquisition sessions (see Figure 1.1). Additionally, massed practice led to an improvement between sessions, while the distributed practice condition led to a decrease in performance level creating an opposite between session effect for trial distributions.

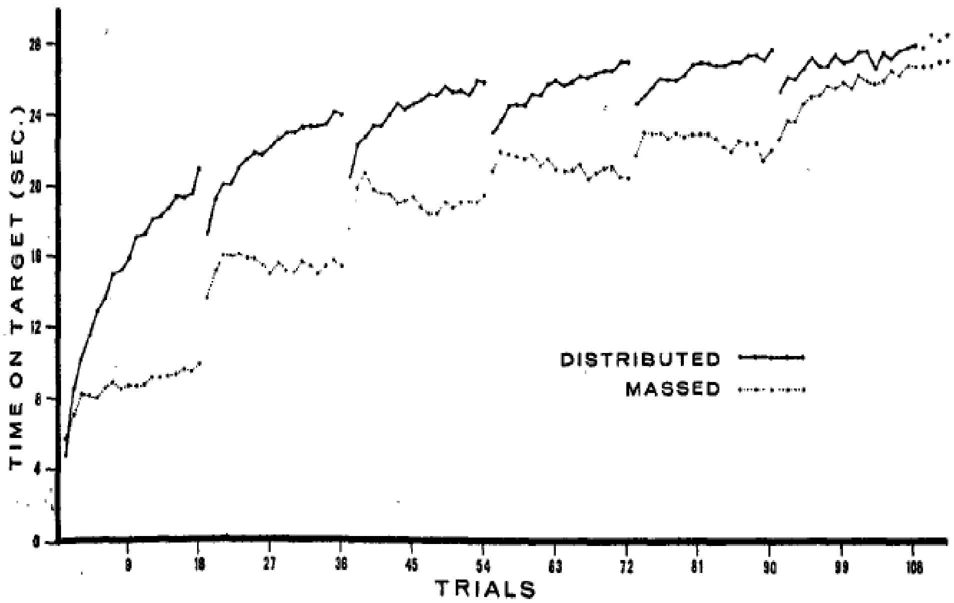

Figure 1.1. Trial distribution effect across 5 days of practice on a pursuit rotor task (from Adams, 1952).

Investigations of the distribution of practice sessions have shown similar findings to that of trial distribution (Baddeley & Longman, 1978; Shea, Lai, Black, & Park, 2000), with longer distribution time between practice sessions, up to 24 hr, resulting in improved performance on a transfer test. Baddeley and Longman (1978) showed enhanced performance and retention on a keyboard typing task when participants performed a single one-hour session per day rather than multiple or longer sessions per day. However, the interaction of *both* trial and session distribution effects has not received systematic study.

Motor Memory Consolidation

Over a century ago, Muller and Pilzecker (McGaugh, 2000) proposed a process termed consolidation to understand the time-course of the growth of memory stability with learning (Leckner et al., 1999). The preservation-consolidation hypothesis identified processes that underlie the transition of a newly learned memory to a stable state that is resistant to disruption (McGaugh, 2000). Subsequently, there have been numerous investigations of the process(es) involved in converting a fragile memory to a stable memory that will withstand interference or degradation.

The acquisition of a new skill can be diminished if another skill interferes prior to complete stabilization of the memory trace (ABA paradigm). Brashers-Krug, Shadmehr, and Bizzi (1996) were one of the first to show motor skill consolidation in a dynamic adaptation task, where Task B interfered with Task A up to 4 hours following the initial learning session. As the time between learning the two distinctly separate tasks increased, the amount of retroactive interference diminished and allowed for the stabilization of the motor memory for the original task

Expanding on the construct of consolidation, Walker (2005) identified two potential stages underlying the formation of memory: time-dependent memory stabilization and sleep-dependent memory enhancement. The successful nature of the stabilization phase does not exhibit sleep dependencies and shows robustness during the passing of time (Brashers-Krug et al., 1996). However, the task specificity of consolidation stabilizing process is unclear because other skills do not show durability to interference even after 24 hours that includes sleep (Caithness et al., 2004; Goedert & Willingham, 2002; Blischke, Erlacher, Kresin, Brueckner, & Malangre, 2008).

The second stage of consolidation identified by Walker (2005) proposes an 'off-line' enhancement of motor memory between sessions that is sleep-dependent. After initial training and a night of sleep, participants performed faster and more accurately at tapping sequences. The 'off-line' enhancement in finger tapping (Walker, Brakefield, Morgan, Hobson, & Stickgold, 2002; Korman, Raz, Flash, & Karni, 2003) or sequence learning (Robertson, Pascual-Leone, & Press, 2004) manifests over a night of sleep resulting in improved performance without any additional physical practice. Additionally sleep-dependent procedural skill learning correlates with the amount of stage 2 NREM (Kuriyama, Stickgold, & Walker, 2004). Being deprived of sleep greatly reduces the gains in performance suggesting that these off-line improvements are supported by neurophysiological changes in brain processes that occur during sleep (Maquet, Schwartz, Passingham, & Frith, 2003). Similar to stabilization, memory enhancement is task dependent in that it is present in finger-tapping task and sequence learning but not in rotary pursuit and arm-reaching tasks (for reviews see Robertson & Cohen, 2006; Vertes, 2005).

Human memories have been classified into two broad types: declarative memory that encodes facts, events, and names; and procedural memory for the performance of skills (Cohen & Squire, 1980). Overlapping this classification is another categorization representing the awareness of acquisition (Song, 2009). In terms of consolidation processes, skills that require participants to learn a sequence explicitly (intentionally) appear to be different from skills where implicit learning (unintentionally) occurs (Robertson et al., 2004; Cohen, Pascual-Leone, Press, & Robertson, 2005). Thus, during sequence learning, if a participant's awareness of the sequence being learned is eliminated, the 'off-line' enhancement can occur during the waking hours of the day in addition to overnight enhancement (Press, Casement, Pascaul-Leone, & Robertson, 2005; Hotermans, Perigneuz, Maertens de Noorhout, & Maquet, 2006). The time-course for 'off-line' enhancement in implicit learning has been shown to take longer than 15 min between testing and re-testing; improvement in performance begins to manifest after 4 hr. Two important features emerge from these studies: (1) an individual's awareness of learning a new skill is an important factor in off-line learning; and (2) 'off-line' learning is not exclusively sleep-dependent but can also be time-dependent (Robertson et al., 2004).

The 'off-line' enhancement in certain newly acquired skills has been shown to improve without any additional practice. However, the gains observed between practice sessions may be an experimental artifact combined with issues relating to the method of analysis (Rickard, Cai, Rieth, Jones, & Ard, 2008). First, reducing the data to block averages and group averages can disguise the learning effects while it also masks the multiple processes involved during skill acquisition (Newell, Mayer-Kress & Liu, 2001). Second, the massed trials practice condition can lead to a gradual increase in fatigue throughout the sessions (Hull, 1943) that could potentially lead to a decrement in performance at the end of the session, which would compromise performance level as an index of the degree of learning.

Time Scales in Motor Learning

The traditional analysis strategy of learning theory uses averaged data represented in a power law function that masks the phenomena of persistent and transient processes of change (Newell & Rosenbloom, 1981). Representing learning data through a single power law causes the independent processes that occur in learning to become superimposed making it difficult to isolate their contribution to behavior. By investigating the time-dependent variables of practice as related to consolidation and learning, the time scales of performance behaviors can be revealed and identified. Each time scale is hypothesized to reflect a unique exponential function that defines the characteristics of the respective process associated with performance dynamics. Newell et al. (2009) have constructed a two time scale model that reflects separate processes: one fast, transient change of warm-up decrement (Adams, 1952) and the other representing the slow-persistent learning effect. The following equations represent the two time scale model shown in Figure 1.2:

Slow Time Scale: $V_s(n) = V_{inf} + \alpha_s e^{-\gamma_s n_j}$ (1)

Fast + Slow Time Scale: $V_f(n) = V_{inf} + \alpha_s e^{-\gamma_s n_j} + \alpha_f e^{-\gamma_f (n - n_{j-1})}$ (2)

V_{inf} depicts the fixed point of goal toward which the participant is trying to achieve. Total trials accumulated throughout all practice sessions is represented by *n* and the practice day is notated by n_j. Figure 1.2A shows the fast and slow time scales when plotted independently to illustrate the contributions of the adaptation and learning processes. In addition, two sample data sets (Figure 1.2B & 1.2C) are fitted with Equation 2 to illustrate the flexibility of the model to various performance dynamics that occur during practice.

The two time scale model represents the observed performance dynamics as a superposition of a slow persistent changing time scale of learning and a fast transient improvement of adaptation (Newell et al., 2009). During each practice session the superposition of the two different characteristic exponential functions describes the performance improvement as well as or better than a single power law or a single exponential function that does not consider the separation of learning and performance processes. The adaptation process includes warm-up decrement on subsequent practice sessions that reverses its sign, thus degrading the performance level during the initial trials. If appropriately modeled as a function of time, the warm-up process would continuously degrade as time passes between sessions.

Conversely, the slow time scale of learning continues to advance toward the task relevant goal state throughout time. In line with the consolidation view, the learning process that is included in the Newell et al. (2009) model remains active between sessions that could potentially lead to an 'off-line' enhancement but the appropriate time constant must be applied to the model to be able to address the time-course of memory formation between sessions. Since both the learning and warm-up processes have different rates of change, the function infers that both are active simultaneously within and between sessions.

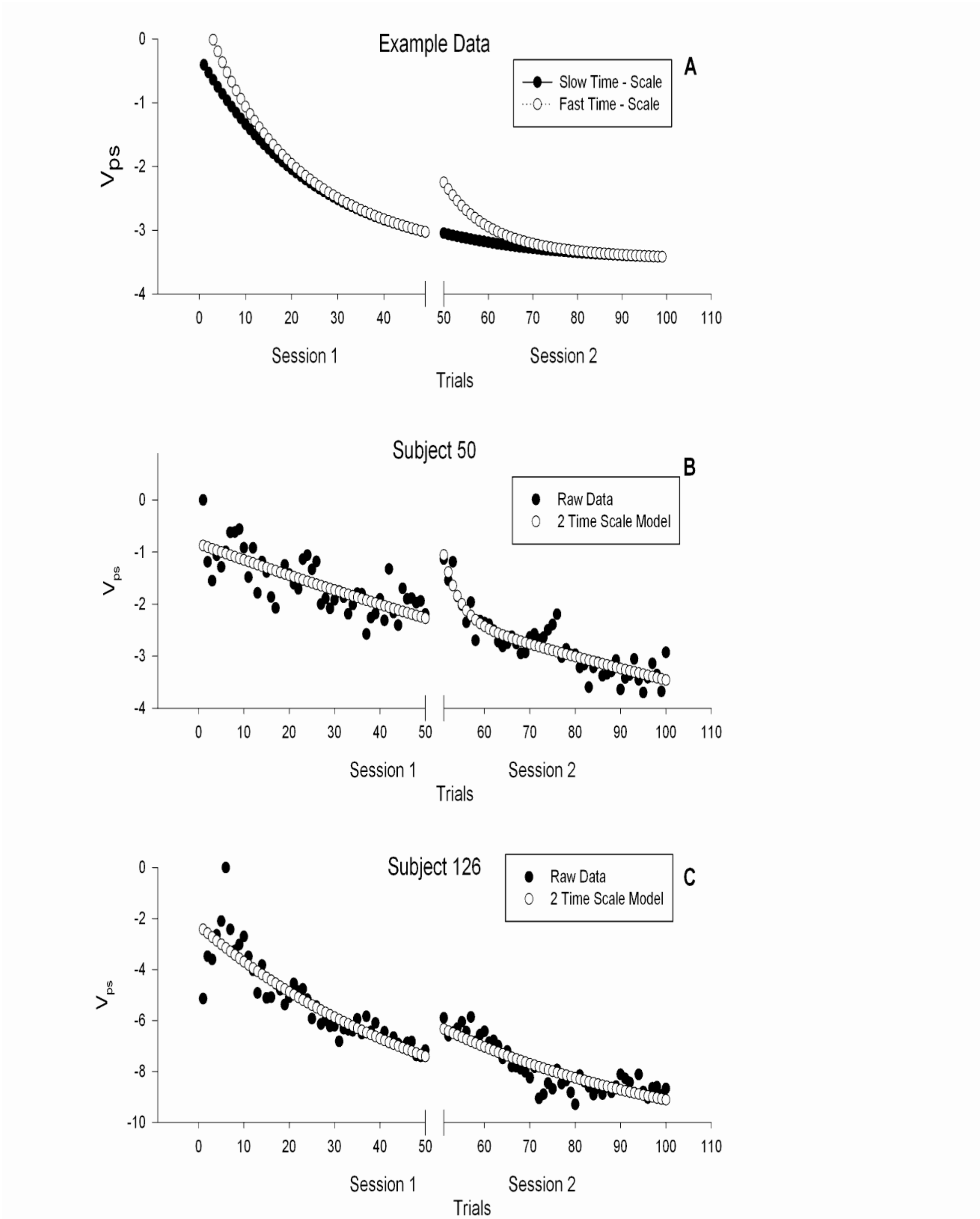

Figure 1.2. Illustration of two time scale model. (A) depicts the separate process of learning and adaptation plotted independently. (B) and (C) show qualitative fits to two different learning data sets.

The six parameters within the model represent the different contributions to learning and adaptation that are active during motor skill acquisition. The first component (V_{inf}) of the model is indicative of the fixed point attractor that is representative of each individual's performance level. Within the slow time scale component, separate parameters represent the growth rate (γ_s) during and between sessions while the coefficient parameter (α_s) specifies the amount of improvement found during the practice session on learning. The parameters within the fast adaptation components ($\gamma_{f \text{ and }} \alpha_f$) are identical to that of the slow time scale, but on a different time scale. However, an additional parameter (α_{f2}) is introduced to the model to represent different rates of improvement on subsequent practice sessions when compared to the initial session of acquisition trials. During the initial acquisition session, multiple sources that contribute to the adaptation time scales, whereas during subsequent sessions the major contributor to the adaptation process is most likely to be represented by a warm-up process (Figures 1.2B and 1.2C) that is best represented by the sixth parameter of the model.

The traditional problem of distinguishing between learning and performance is based on the challenge of the best way to measure learning. Within the performance dynamics are many sources of transient, rapidly changing properties that represent distinctively different time scale parameters in addition to a persistent learning effect that takes place on a completely distinctive time scale. In the multiple time scale model, warm-up decrement (Adams, 1961) accounts for a loss of specific task relevant postural and system adjustments present at the beginning of practice sessions that leads to rapid performance improvement that may or may not influence learning. Identification of these time scale phenomena to the performance dynamics offers behavioral insight into the processes of learning that is obscured in the typical power law function.

Focus of the Experiments

The between practice learning, termed 'off-line' enhancement, has only been quantified utilizing a single retention measure rather than a time-course evolution revealed in time series analysis. The simple retention variable previously used to measure 'off-line' enhancement fails to account for the transient performance dynamics of adaptation. Therefore, the isolation of the transient, rapid, fluctuation parameters allows for a better estimation of the persistent learning effect.

The two time scale model of Newell et al. (2009) isolated the slow persistent learning process during and between practice sessions and a fast, adaptive process at initial performance that allows the separation of performance and learning dynamics. In line with the consolidation literature, the hypothesis is that learning effects take place both within and between practice sessions. Warm-up decrement is not the only transient property that could be included in the multiple time scale model (Karni et al., 1998) but the inclusion of other properties requires the superposition of additional exponential processes. One potential additional source of transient behavior that could be represented is fatigue that would characterize a decrement in performance as reactive inhibition increases throughout a practice sessions.

In the studies reported here, we manipulated the between-trial and between-session time intervals to investigate the effects of distribution of practice on consolidation and the persistent performance changes through learning. The two time scale model (Newell et al., 2009) will be used to decompose the transient performance variable of warm-up from the persistent process of learning allowing for a different measure of learning than typically observed. The process of analyzing learning curves on multiple time scales over the entire time course of acquisition moves away from the traditional absolute performance retention or transfer measurement employed in most motor skill learning experiments

CHAPTER 2. INFLUENCE OF PRACTICE SESSION DISTRIBUTION ON MEMORY FORMATION

Introduction

The time-course of memory formation has indicated that 'off-line' enhancement effects become evident after a 4 hr interval post-initial training sessions (Press et al., 2005). Furthermore, the added benefit of particular sleep rhythms may be a factor to the gains seen during consolidation when no addition practice is undertaken (Walker, Brakefield, Hobson, & Stickgold, 2003). The growth of the performance score was investigated by manipulating the time interval between practice sessions under the same distribution of trials within a condition. To measure the time evolution of a new motor skill memory, a subsequent practice session was scheduled 2 hr, 4 hr or 24 hr post-initial acquisition session; also a control group had no break between practice sessions.

Methods

Participants

Thirty-two adult volunteers (M = 27.1 years, SD = 3.6) participated in this study. The participant's handedness was determined by self-reports of the hand they normally write with. None of the participants had previous experience with star tracing or reported any extensive experience using a graphics tablet. The experimental procedures were approved by the Pennsylvania State University Institutional Review Board. Informed consent was provided by all participants.

Apparatus

The experimental apparatus was a Wacom Cintuq 21UX graphics tablet, stylus, and laptop PC. The video output of the custom program was displayed directly onto the graphics tablet screen and reflected the motion of the graphics pen tip. The sample rate was 200 Hz for the collection of two-dimensional position data.

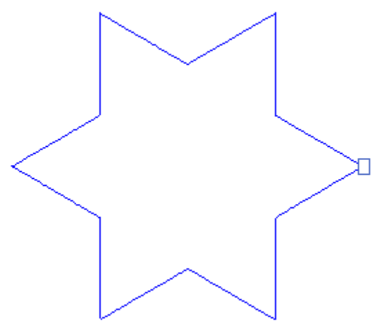

Figure 2.1. Schematic of star. Participants began and ended each trial in the small right-hand box and traced the star in the counter-clockwise direction. Performance score feedback was visually displayed after each trial.

Task

The task in this study was to reduce the space-time performance error to a minimum in attempting to draw over a star shape (see Figure 2.1) in a particular time. The star was similar in size and shape to the star used by Snoddy (1926) and Stratton et al. (2007). The star shape was 300 mm in diameter. Participants were randomly assigned to one of 4 groups with different inter-session practice intervals. The inter-session intervals were no-break, 2 hr, 4 hr, and 24 hr.

Procedures

The task was to learn to trace the star shape on the graphics tablet (Figure 2.1). To begin a trial, participants moved the stylus into the small box on the right hand side of the star and waited for an auditory beep. A sound indicated the start of the trial. The participant traced in a counter-clockwise direction around the star and finished the trial when the pen tip returned to the small box. Another sound indicated the end of each trial. At the end of each trial, participants received a visually displayed performance score measure that was based on a task criterion that weighted equally space and time to the performance score. There was a 15s rest interval between each trial and after the rest interval the participant pushed the button on the stylus to begin the next trial. For each session the participant performed 50 trials that took approximately 30-45 min. Each participant performed 2 testing sessions spaced according to the inter-session group intervals.

Performance Score

The performance score measure was based on the segment of the speed-accuracy curve that gave equal weight to space and time in the criterion score. The performance score was derived from the following equation:

$$PS_i = (a * T_i + b * E_i)/(a * t + b * e) \qquad (3)$$

Where $_i$ indicates the i^{th} trial and *PS*, *T*, and *E* represent the performance score, tracing time and spatial error, respectively. The weighting for time is the coefficient *a* while *b* is the weighting coefficient for the spatial error component. Letters *t* and *e* in Equation 3 represent normalization parameters.

Weighting parameters a and b. Pilot data from three participants not in the experimental groups constructed the average speed-accuracy curve to determine the weighting parameters of the performance score. Each participant performed 25 trials emphasizing three different regions of the speed-accuracy curve; speed emphasis, accuracy emphasis, and speed with low error emphasis. An averaged speed-accuracy curve was fit to the data. To obtain equal emphasis on speed and accuracy a line with a negative 45 degree slope was fit to a point along the pilot curve. The line was located within the middle segment of the averaged curve at a task time of 15 s. Based on the slope of the curve at this point, an a:b ratio for the experiment was determined and input into Equation 3 as the weighting parameters to calculate the performance score for each trial.

Normalization parameters t and e. From the pilot data, the fastest time and least spatial error from all the trials were used as the normalization parameters values in Equation 3.

Data Analysis

The performance score and task time were evaluated as a function of practice interval. A similar analysis was used to measure the amount of ‘off-line’ learning that occured between sessions. In addition, the individual participant data were fitted to the two time scale model (Newell et al., 2009) that includes 6 parameters in order to distinguish the contribution of adaptation and learning to the performance dynamics.

Separate ANOVAs were executed on the individual parameters of the model to evaluate the learning and adaptation within each session's performance. An alpha level of .05 was used for all statistical tests.

Results

Performance Score

Figure 2.2 shows the mean performance score as a function of trial blocks for the different intervals between practice session groups. The performance score was the task criterion and the main variable for analysis. The individual components of task time and spatial error were also investigated to determine the influence each had on the pathway of change in the performance score across the learning sessions.

The performance score was analyzed by a 4 (practice session interval) x 2 (session) X 10 (blocks) mixed design ANOVA. Figure 2.2 illustrates a significant block effect, $F(9,252) = 31.04$, $p < .001$, and a significant session effect, $F(3, 28) = 47.14$, $p < .001$. The block x group and session x group interactions failed to show a significant difference, $F(27,252) = 1.07$, $p > .05$ and $F(3, 28) = 1.88$, $p > .05$, respectively. The triple interaction of group x session x block was not significant, $F(3,28) = .86$, $p > .05$. The main effect of practice session interval was not significant, $F(3,28) = .86$, $p > .05$.

The quantification of 'off-line' enhancement, calculated by the change in performance between sessions (Block 11 – Block 10) did not differ significantly between the practice session interval groups, $F(3, 14) = 1.87$, $p > .05$. There were small increases in performance scores for all groups except the 4 hr-break group that showed the greatest decrement in performance. The performance score at the beginning of session 2 was not significantly different between groups, $F (3, 28) = 1.38$, $p > .05$. There was also no effect of practice session interval at the end of session 2, $F (3, 28) = .04$, $p > .05$.

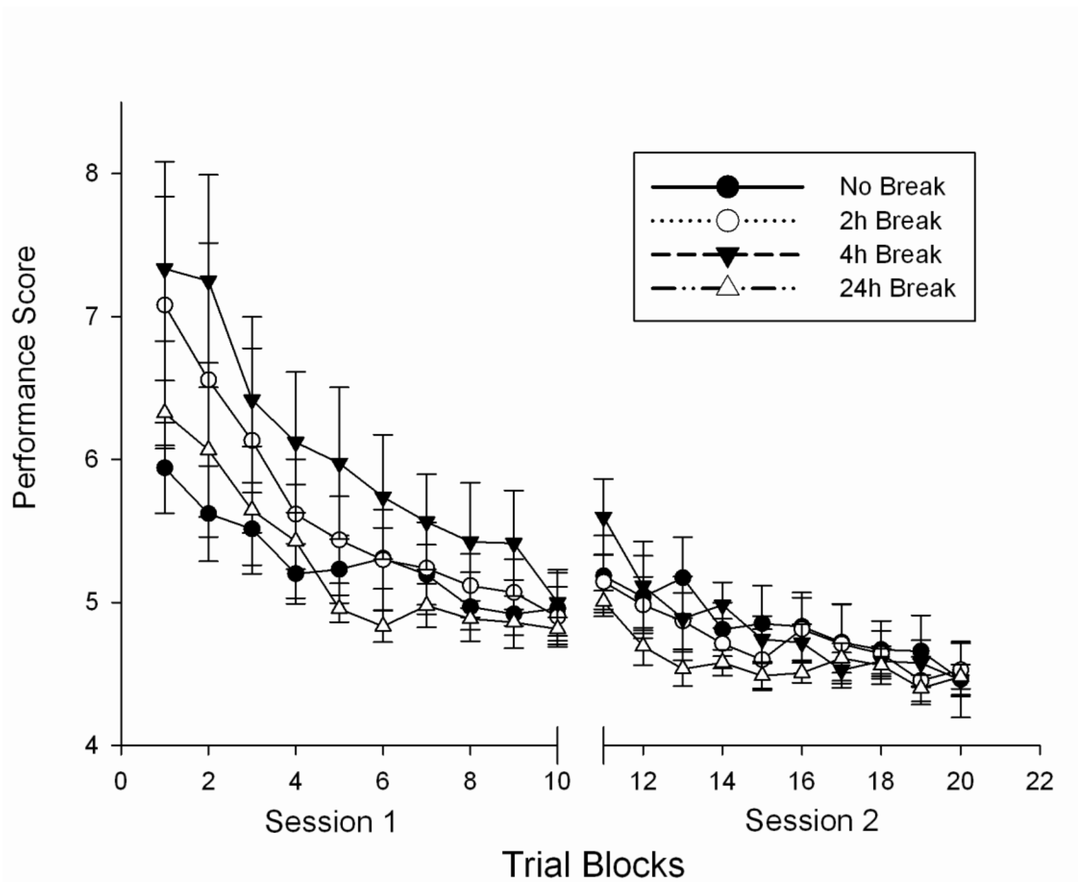

Figure 2.2. Performance score as a function of trial block across both sessions. Trial blocks consist of a 5 trial average. Interval between sessions indicated by group. Error bars represent one standard error.

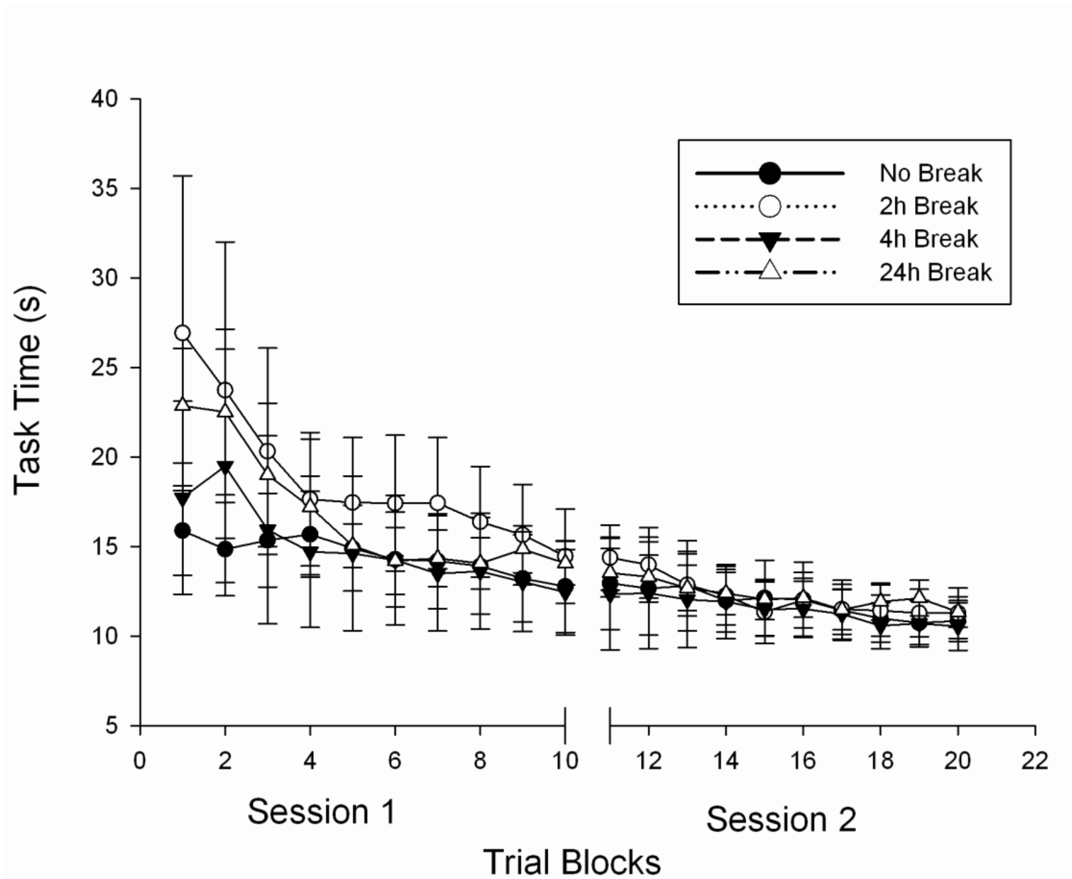

Figure 2.3. Task time as a function of trial block across both sessions. Trial blocks consist of a 5 trial average. Error bars represent one standard error.

Task Time

A 4 (practice session interval) x 2 (session) x 10 (blocks) mixed design ANOVA was used to examine the effect of practice on task time. Large disparities in task time across the practice session interval conditions were present in the early blocks of practice, but these converged to near identical task time indicating the effectiveness of the feedback score to channel participants to a preferred location on the speed-accuracy trade-off curve (Figure 2.3).

Analysis of the task time across all blocks showed a significant difference, $F(9,252) = 170.44$, $p < .001$, and the session effect also showed a significant difference, $F(1, 28) = 12.17$, $p < .001$. The block x group and session x group interactions failed to show a significant difference, $F(27,252) = .47$, $p > .05$ and $F(3,28) = .46$, $p > .05$, respectively.

Spatial Error

The spatial error score was analyzed through a 4 (group) x 2 (session) x 10 (block) repeated measures ANOVA. Spatial error showed a significant difference across the blocks of practice, $F(9,252) = 5.87$, $p < .05$. The session effect on spatial error failed to show a significant difference, $F(1,28) = .95$, $p > .05$. The block x group interaction approached significance but did not reach statistical difference, $F(27,252) = 1.45$, $p = .08$. The session x group failed to show a significant difference, $F(3,28) = 1.14$, $p > .05$. Practice session interval effect was not significant, $F(1,28) = .70$, $p > .05$.

CHAPTER 3. MASSED TRIALS INFLUENCE ON THE TIME COURSE OF MEMORY FORMATION

Introduction

Rickard et al. (2008) proposed that the massing of practice trials could result in greater ‘off-line’ enhancement due to reactive inhibition build-up, and the decrement in performance during the later trials of session 1. Under massed trials condition, the hypothesis is that a greater amount of reactive inhibition would create a decrement in performance during the later segments of the initial acquisition session leading to a discrepancy between performance and learning levels at the final trials. Consequently, a larger ‘off-line’ enhancement could be evident if typical learning measures were used. The two time scale model (Newell et al., 2009) provides a strategy to test whether this performance difference only happens on the fast, transient time scale and not on the slow learning time scale. The massed trials condition incorporated into Experiment 2 tested the effects of the practice session interval under the traditional distribution of practice analysis.

Methods

Participants

Twenty-four adult volunteers (M = 27.1 years, SD = 4.1) participated in this study. The participant’s handedness was determined by self-reports of the hand they normally write with. None of the participants had previous experience with star tracing or reported any extensive experience using a graphics tablet. The experimental procedures were approved by the Pennsylvania State University Institutional Review Board. Informed consent was provided by all participants.

Apparatus

The experimental apparatus was the same graphics tablet from Chapter 2. The sample rate was 200 Hz for the collection of the two-dimensional position data.

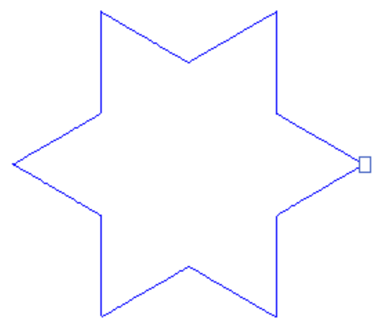

Figure 3.1. Schematic of star. Participants began and ended each trial in the small right-hand box and traced the star in the counter-clockwise direction. Performance score feedback was visually displayed after each trial.

Task

The task in this study was to reduce the space-time performance error to a minimum in attempting to draw over a star shape (see Figure 3.1). The star was identical to the one used in Chapter 2. Participants were randomly assigned to either a no-break or a 24 hr – break practice session interval.

Procedures

The task was to learn to trace the star shape on the graphics tablet (Figure 3.1). To begin a trial, participants moved the stylus into the small box on the right hand side of the star and waited for an auditory beep. A sound indicated the start of the trial, the participant traced in a counter-clockwise direction around the star and finished back in the small box. Another sound indicated the end of each trial. At the end of each trial, participants received a visually displayed performance score measure that was based on a task criterion that weighted equally space and time to the performance score. Participants could begin the next after the performance score was displayed. This created a massed trials practice condition where minimal rest interval happen between each successive trials. For each session the participant performed 50 trials that took approximately 30-45 min. Each participant performed 2 testing sessions spaced according to the inter-session group intervals.

Performance Score

The calculation of the performance score was identical to that outlined in Chapter 2. The same weighting and normalization parameters were also used in this study. The derivation of the performance score can be found in Equation 3.

Data Analysis

The performance score, task time and spatial error were evaluated as a function of practice interval. A similar analysis was used to measure the amount of 'off-line' learning that occurs between sessions. In addition, the individual participant data were fitted to the two time scale model (Newell et al., 2009) that includes 6 parameters in order to distinguish the contribution of adaptation and learning to the performance dynamics. Separate ANOVAs were executed on the individual parameters of the model to evaluate the learning and adaptation within each session's performance. An alpha level of .05 was used for all statistical tests.

Results

Performance Score

The mean performance score as a function of trial blocks for the two practice session interval groups is shown in Figure 3.2. A 2 (practice session interval) x 2 (session) x 10 (blocks) mixed design ANOVA of the performance score revealed a significant effect of block, $F(9, 198) = 18.08$, $p <0.001$) and sessions, $F(1,22) = 24.15$, $p < .01$. Figure 3.2 shows that learning occurred within both sessions. The block x group interaction showed a significant difference, $F(9,198) = 2.73$, $p < .01$, however, the session x group interaction was not significant, $F(1,22) = 2.22$, $p > .05$. The practice session interval effect was not significant, $F(1,22) = 1.92$, $p > .05$.

The measurement of 'off-line' enhancement (Block 11 – Block 10) with massed trials showed no significant difference between the no-break and 24-h break groups, $F(1, 22) = 1.07$, $p > .05$. The group that had no-break between sessions continued to show improvement of the performance score based on the calculation of 'off-line' enhancement, whereas the 24 hr-break group showed a decrement in performance.

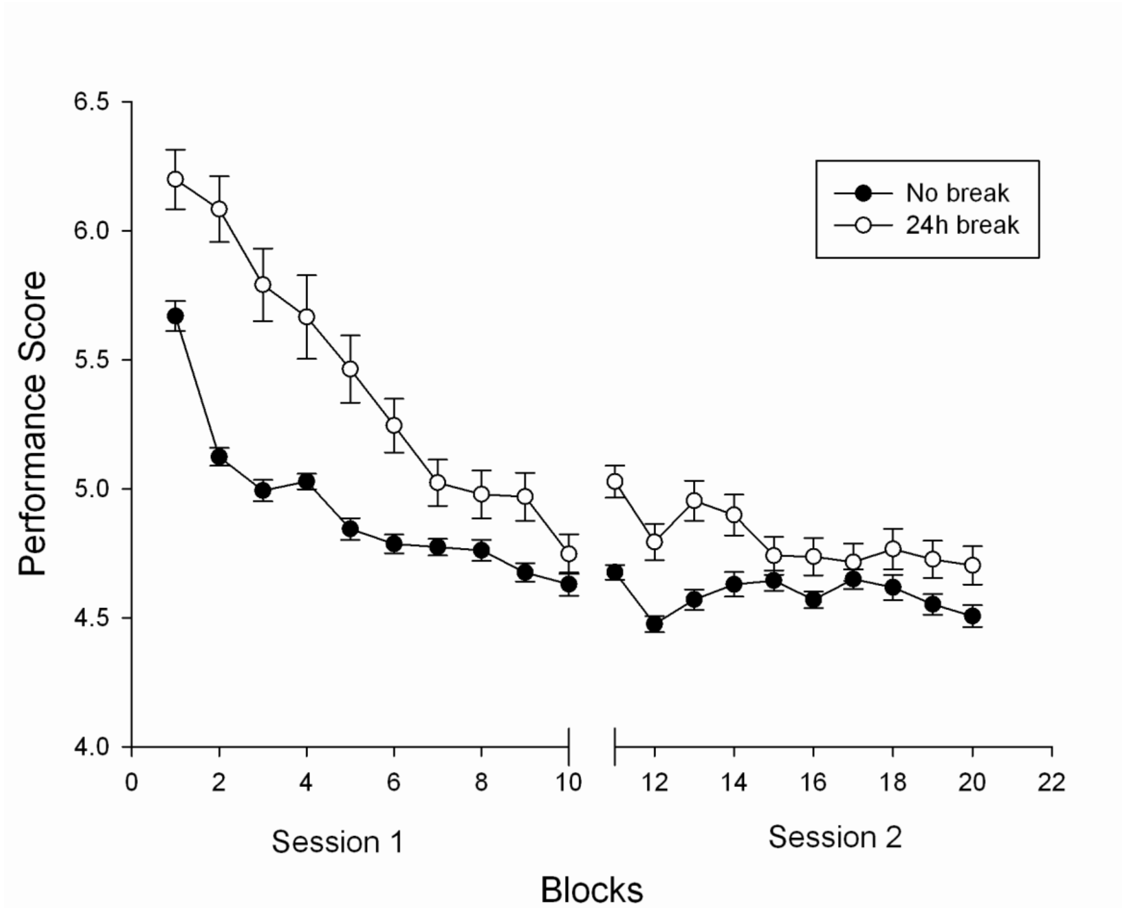

Figure 3.2. Performance score under massed practice condition. Trial blocks consist of a 5 trial average. Error bars represent one standard error.

Task Time

Similar to Experiment 1, a 2 (practice session interval) x 2 (session) x 10 (blocks) mixed design ANOVA of the task time showed a significant difference for the block effect, $F(9,198) = 9.52$, $p < .001$, and a significant difference for the session effect, $F(1,22) = 11.37$, $p < .01$ (see Figure 3.3). The triple interaction of session x block x group showed significance, $F(9,198) = 1.87$, $p = .05$. The main group effect failed to reach significance, $F(1, 22) = 3.46$, $p > .05$.

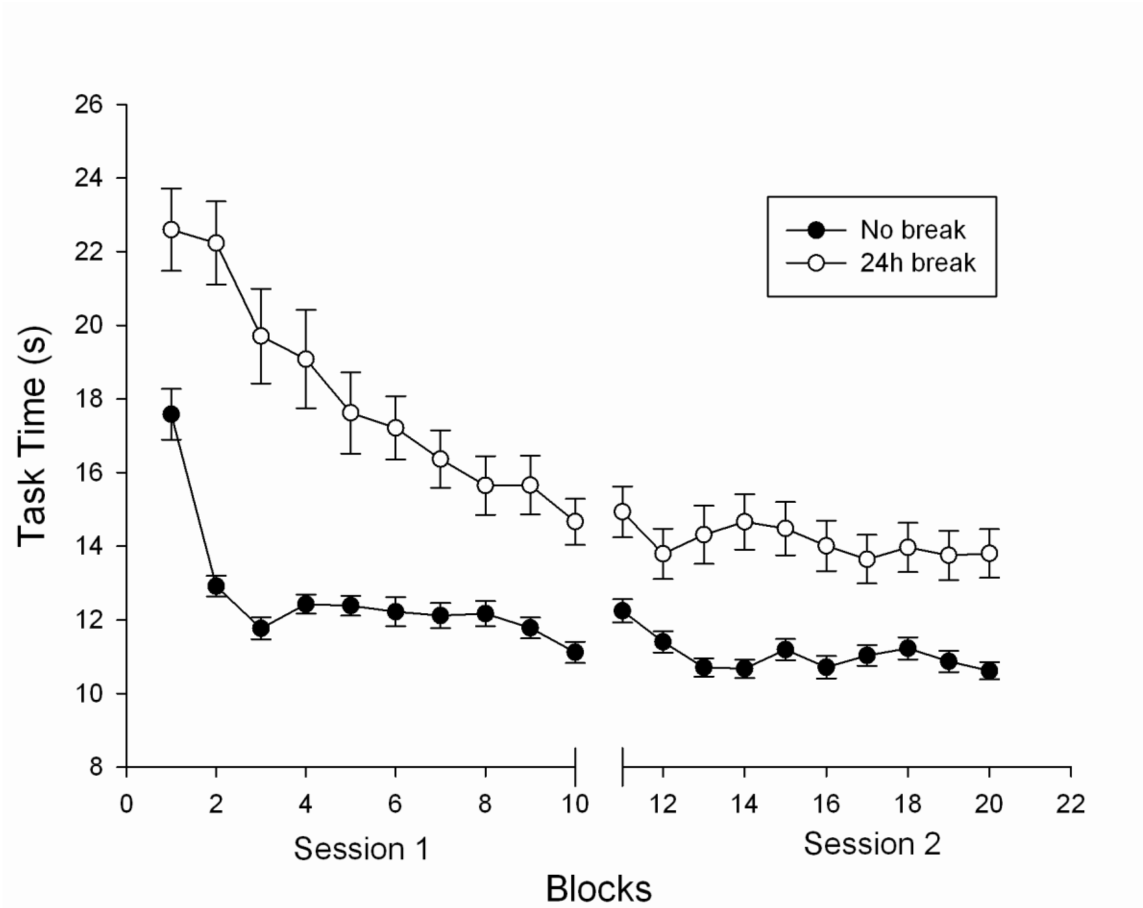

Figure 3.3. Task time performance under massed trials condition. Trial blocks consist of a 5 trial average. Error bars represent one standard error.

Spatial Error

Analysis of the spatial error used a 2 (group) x 2 (session) x 10 (blocks) mixed design ANOVA. All of the main effects and the interactions failed to reach a significant difference at the $\alpha = .05$ level.

Integration of Experiments 1 and 2 by Time Scale Analysis

The individual performance score data were fit to the two time scale model (Newell et al., 2009) that included 6 parameters (V_{inf}, α_s, γ_s, α_f, α_{f2}, γ_f). The no-break (D-M; distributed trials with massed sessions) and 24 hr-break (D-D; distributed trials with distributed sessions) practice session intervals from Experiment 1; and the no-break (M-M; massed trials with massed sessions) and 24 hr-break (M-D; massed trials with distributed sessions) practice session intervals from Experiment 2 were included for the main analysis. These 4 groups provided a spectrum of distribution schedules across trials and sessions. The data from the 2 hr- and 4 hr- break practice session interval were also fit to the two time scale model for separate analysis to investigate the adaptation process of warm-up decrement across different practice session intervals.

Table 3.1 shows the group mean of the six parameters within the model from both experiments. The V_{inf} asymptote value was not significant, $F(3,36) = 1.31$, $p > .05$. The individual pathways of change led some participants to have more absolute improvement represented by a large asymptote value. On the slow time scale components, both $\alpha_{s \text{ and }} \gamma_s$ were not significant between the groups, $F(3, 36) = 1.83$, $p > .05$; $F(3, 36) = .88$, $p > .05$, respectively.

Within the adaptation time scale, the α_f parameter did not differ during the initial session's performance as evident in figure 3.4, $F(3, 36) = 1.52$, $p > .05$. However, the warm-up parameter of the second session (α_{f2}) showed a significant difference, $F(3, 36) = 4.95$, $p < .01$. A Tukey HSD post hoc analysis showed that the D-D group was higher than the M-M group. The γ_f parameter showed a significant difference, $F(3,36) = 2.66$, p

= .05. A Tukey HSD post hoc analysis revealed the M-M had a significantly higher value than the D-M.

Table 3.1.

Two time scale model parameters (averaged within groups) used to analyze performance and learning contributions.

	Experiment 1					
Group	V_{inf}	α_s	γ_s	α_f	α_{f2}	γ_f
No-break	-3.9597	2.906638	0.130675	0.582763	0.834313	0.229563
2h-break	-6.1069	3.400861	0.114557	2.948847	0.990264	0.102877
4h-break	-6.12948	2.870569	0.090954	2.65553	1.520448	0.237411
24h-break	-4.07966	2.125488	0.040875	2.20155	1.598025	0.359825

	Experiment 2					
Group	V_{inf}	α_s	γ_s	α_f	α_{f2}	γ_f
No-break	-2.4428	1.1188	0.0713	2.0157	0.5308	0.5425
24h-break	-3.6929	2.2619	0.0991	1.3340	1.2084	0.4416

The massed (M-D and M-M groups) and distributed (D-D and D-M groups) trial conditions were analyzed through five separate one-way ANOVAs run on each of the parameters (except V_{inf}) of the model to investigate the effect of trial distribution on the parameters of adaptation and learning (Figure 3.5). The γ_f was the only parameter to reach statistical significance, $F(1,38) = 6.60$, $p < .05$. All other parameters showed no statistical significance.

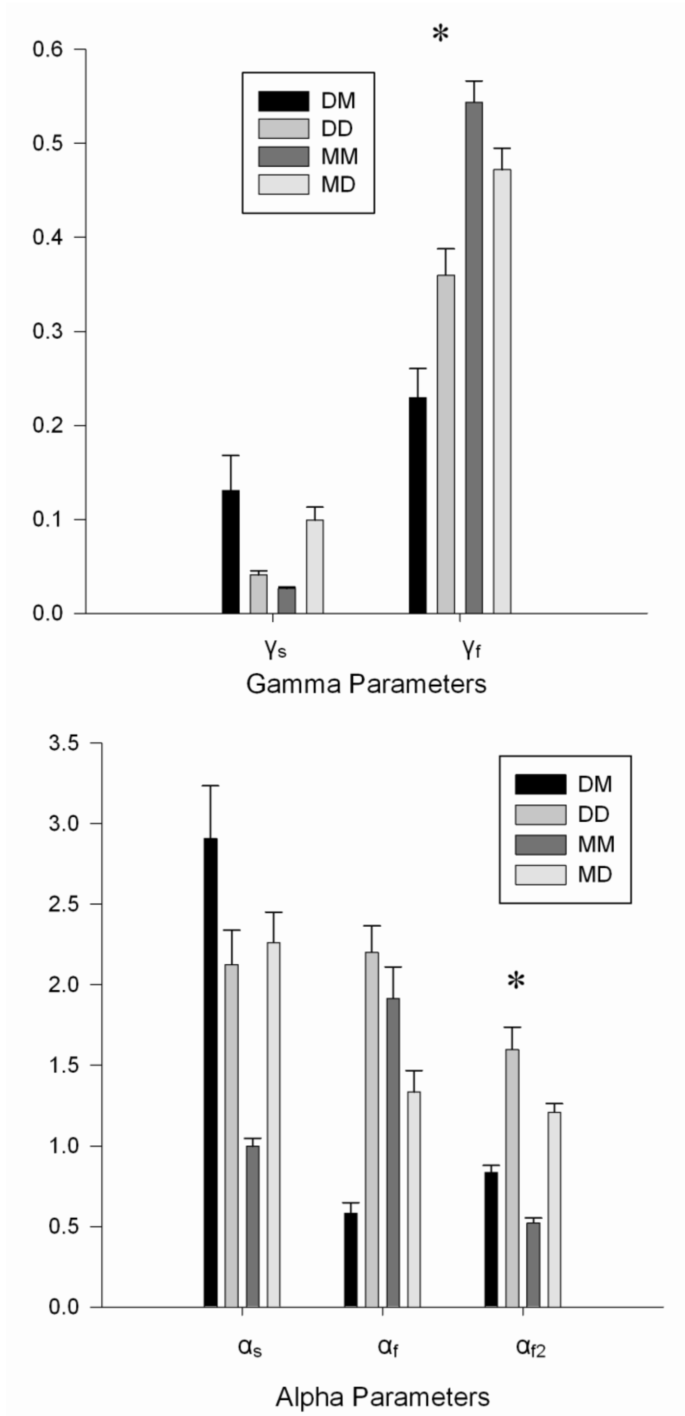

Figure 3.4. Gamma (top) and alpha (bottom) parameters from two time scale model fit. Error bars represent one standard error.

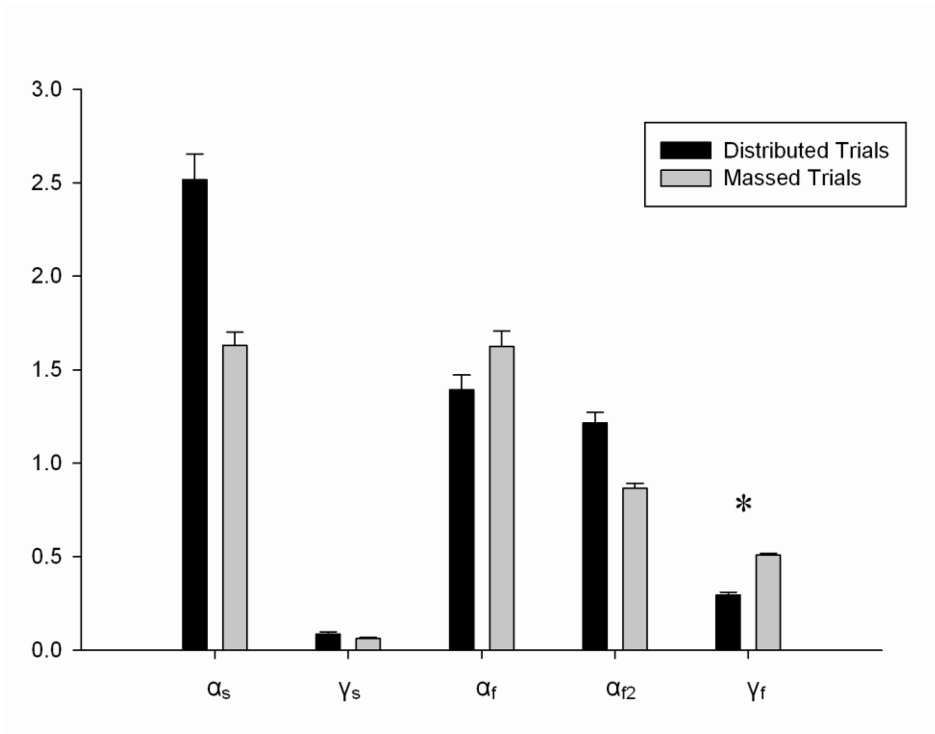

Figure 3.5. Practice trial condition effect on five parameters from two time scale model fit. Error bars represent one standard error.

Additionally, the effect of session distribution on the parameters of learning and adaptation were investigated for the six components of the time scale model. Multiple one-way ANOVAs were run on each parameter with practice session interval as the main factor. The influence of the practice session interval showed no statistical difference on all the parameters of the model expect for the warm-up coefficient on session two performance (Figure 3.6). The 24 hr practice session interval showed a significantly higher value for α_{f2} parameter, $F(1,38) = 9.93$, $p < .01$.

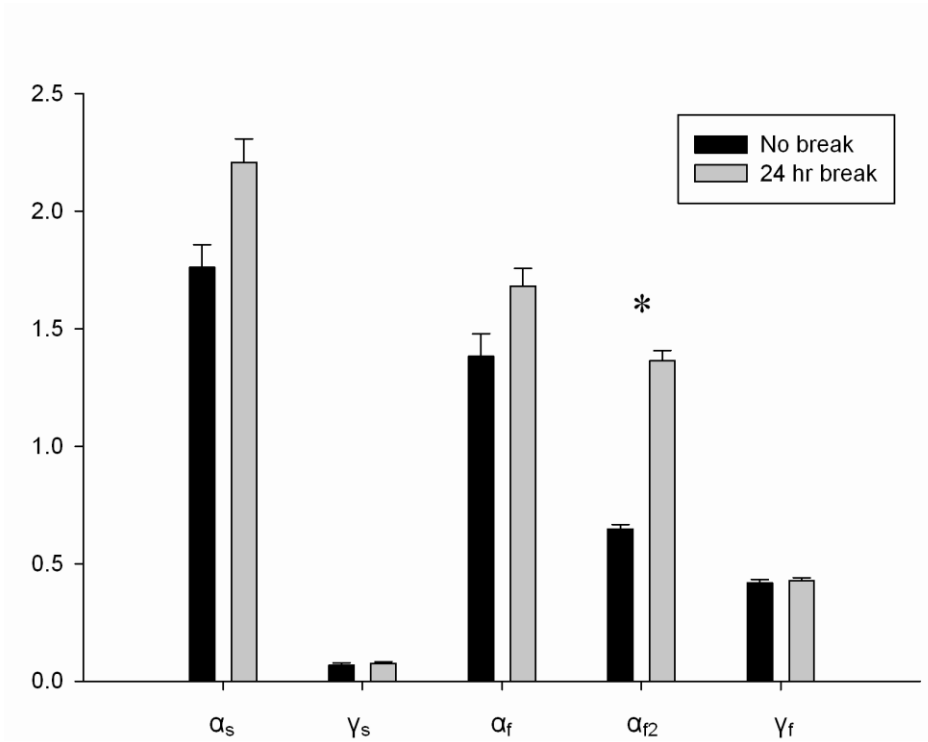

Figure 3.7. Practice session interval effect of five parameters from the two time scale model. Error bars represent one standard error.

The final analysis included all practice session intervals from Experiment 1 to evaluate the α_{f2} parameter on the second session. Although the trend between the groups in Experiment 1 failed to reach significance, a progressive increase of the α_{f2} parameter occurred as the time between sessions increased as shown in Table 3.1.

CHAPTER 4. General Discussion

The experiments presented here sought to investigate two processes – adaptation and learning – with respect to the time course of memory formation under different practice schedule distributions. By examining the performance dynamics within a two time scale model (Newell et al., 2009), the slow, persistent time scale of learning was distinguished from a fast, transient time scale of adaptation. A number of trial and session schedule distributions were investigated to understand the practice schedule effects on learning and adaptation, and investigate the time course of off-line enhancement reflected through consolidation. The results showed that in this speed-accuracy drawing task different practice schedule distributions influenced the process of adaptation to a greater degree than the learning process. Furthermore, the typical measurement of off-line enhancement is confounded due to the warm-up process that is evident during the early trials of a retention/acquisition session.

The fast, adaptation time scale was influenced by both trial distribution and session interval, whereas the learning time scale remained relatively constant supporting the results of Lee and Genovese's (1988) meta-analysis showing that the massed practice condition is largely a performance variable and has little influence on learning. The meta-analysis showed an effect for a decrement in performance for the massed trials condition on continuous tasks (Adams, 1952; Bourne & Archer, 1964; Adams & Reynolds, 1956; Digman, 1964). In contrast, discrete tasks do not show the performance variable effect under the massed condition (Carron, 1969; Lee & Genovese, 1988a). Although the task used in these studies does not fit perfectly into either the discrete or continuous classification, it is clear that the task times from both experiments are longer than the task durations in typical learning studies involving discrete tasks; while on the other hand, conventional continuous tasks (pursuit rotor) use work periods of 30 s or longer. The findings from both experiments would suggest the task to be closer to a discrete movement because there were negligible performance score differences between the massed and distributed trials conditions.

The no-break practice interval groups from both experiments used faster task times, on average, when compared to all other groups (Figures 2.3 and 3.3). This finding implies the knowledge of consecutive practice sessions yields a distinctly different strategy that involves shorter movement times, which in turn leads the participant to complete the practice session in less clock time than others who use longer task times. Attention and motivation may contribute to the participants attempting to complete the practice session in less time. It follows that the strategy used in the two dimensional feedback score from these experiments may be dependent on the time interval between practice sessions. Additionally, large variances in the task times during the early blocks of practice indicated another potential source of strategy selection influencing the dynamics of the performance score measure.

The findings on the adaptation time scale during the second session performance support the warm-up decrement hypothesis (Adams, 1952) and the associated process of restoring the system to the task relevant criterion (Nascon & Schmidt, 1971). All practice schedule distributions showed a warm-up decrement that was dependent upon the time interval between practice sessions. Participants performing with a 24 hr interval between practice sessions exhibited the greatest amount of decrement as measured through the α_{f2} parameter of the time scale model. Conversely, participants with no practice session interval exhibited minimal warm-up decrement. In addition to the time interval between practice sessions, skill level of the task contributes to the amount of decrement during the adaptation process (Newell et al., 2009). Basically, an expert performer will require fewer trials during the warm-up phase than a novice performer, given the same time interval since last practice, though this effect was not tested in the current experiments.

The decomposition of the performance dynamics challenges the typical measurement approach used to quantify the off-line enhancement seen in most consolidation studies. The majority of retention tests take the averaged performance of the initial trials to assess learning, whereas the time scale approach of analyzing individual data across the entire time series emphasizes both the quantity and rate of performance change. The utility of averaging learning curves across participants can have significant ramifications on the rate of learning and potentially alter the parameters within exponential functions so that the composite of the average is not representative of the individual data (Bahrick, Fitts & Briggs, 1957; Brown & Heathcote, 2003; Newell et al., 2001). Our findings show practice distribution effects on the different time scales and confirm that the convenience of averaging across trials can mask the measurement of learning (see Figure 1.2).

Off-line enhancement and warm-up decrement present two conflicting viewpoints to the effects of the time interval between practice sessions. Consolidation, through an off-line enhancement process, supports positive performance gains during a rest period

(Robertson et al., 2004), while warm-up decrement shows reduced levels of performance (Adams, 1952). The use of the two time scale model offers a solution to this discrepancy by separating the distinct processes involved. It is conceivable that not all tasks exhibit warm-up decrement, but to our knowledge there has been little systematic investigations into the generalization of warm-up decrement across a variety of tasks. Identifying the characteristics of off-line enhancement and warm-up decrements over different time intervals will require future investigations to determine the generality of each process.

If improvement does occur without additional practice, off-line enhancement, as evident with averaged data, the potential gains in performance from consolidation may be even greater than recently measured, as long as warm-up is present. However, off-line enhancement makes no attempt to dissociate learning from warm-up decrement which potentially leads to ambiguous measures of retention. Newell et al. (2009) proposed that both adaptation and learning are active simultaneously during and between practice sessions and the evolution of the slow time scale continues to show progress toward the task goal in the absence of practice trials. However, adaptation works on a distinctly different time scale in the opposite direction resulting in a warm-up decrement from rest periods. Therefore, the measurement along the slow-time scale of learning with the transient properties of adaptation removed provides a clearer picture of the persistent nature of memory formation. Future work investigating the time course of consolidation needs to incorporate the decomposition of multiple processes that are active during skill acquisition.

Introducing the time scales of processes into motor learning has slowly merged its way into the literature. However, there are different viewpoints to the representation of the typical two time scale models. Karni et al. (1998) identified a fast, within-session state that induces rapid improvement through trial repetition, and a slow learning effect triggered by practice that produces gradually evolving incremental performance gains that takes hours to become effective. Criscimagna-Hemminger and Shadmehr (2008) proposed that adaptation to an environment creates a highly fragile, fast state memory and through the passage of time is transformed into a slower state that is resistant to disruption; introduction to an interfering task B within a given time window will create competing fast memory states that hinder the task A.

The models of Newell et al. (2009), Karni et al. (1998) and Criscimagna-Hemminger and Shadmehr (2008) each include a slow and fast time scale. However, the key distinction between these two models and Newell et al. (2009) is the time course of activation of both time scales. The two aforementioned models suggest that one time scale (fast) is active during practice sessions and the slow time scale is activate between sessions, whereas Newell et al. (2009) model proposed simultaneous activation of both processes occurring during and between practice sessions. Identification of the multiple time scales across a variety of tasks and environment requires further investigation. The construct of time scales provides opportunities to investigate the nature of memory formation through consolidation and affords a new analytical tool in the measurement of the persistence of learning.

Limitations and Future Research

There were a few limitations in the current experiments. First, the amount of statistical power associated with both experiments is low. Though this may appear to hamper the statistical significance in the results, the overall trend within the participants did not appear to be converging toward a population estimate. In all groups the amount of within-subject variability was high and the between-group variability during session 1 performance was markedly different given nearly identical conditions. Given this fact, a potential future study should investigate the different strategies participants used to minimize the performance score through implicit knowledge of task time and spatial error. The feedback measure combined two dimensions into a single outcome score that participants had to minimize, but the approach to minimizing this score could take place along different dimensions which could influence the amount of learning within and between practice sessions.

Second, the selection of our drawing speed-accuracy task eliminated the direct knowledge and possible control over a specific task time. Therefore, the manipulation of the work/rest ratio did not equally control the amount of inhibition/fatigue across all participants. The greater build-up of fatigue under a strict massed practice condition could lead to a decrement in performance that was not evident in these experiments. Future studies associated with practice schedule distributions should control the work and rest intervals to investigate the influence of trial distribution on the time scales of learning and adaptation.

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