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Delayed Benefits from Spaced Training When Learning a Precision Throwing Task

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Featured Application: Controlling for the performance stabilization during training distribution schedules permits to establish the appropriate amount of practice required to triggers the benefits from spaced training.

Abstract: Spaced training produces gains in performance associated with memory consolidation, which develops between sessions (offline gain). Learning motor skills that require many repetitions may generate a delay in memory formation and in offline gain. We tested the presence of this delay by studying a precision throwing task. Sixteen participants performed 1020 underarm precision throws distributed over four sessions. Eight participants spaced the training by 40-min between-session intervals, while the remaining subjects distributed the practice with 1-day intervals. Memory retention was tested 15 days after training. Differences in accuracy over groups, sessions, directions of throwing movements and blocks of throws were evaluated by analysis of variance. The 40-min group had better performance than the 1-day group after the first two sessions. As the level of skill stabilized, the 1-day group exhibited offline gains, with significant performance improvements during the fourth and retention session. Both medial-lateral and antero-posterior movement directions of throwing contributed to the performance. Initial decrements in performance appeared within sessions for both groups. Overall, when learning a precision throwing task, benefits from spaced training is delayed and occurs as the skill stabilizes. These findings may help to optimize training distribution schedules, particularly for precision motor skills requiring extensive practice.

Keywords: motor skills; memory consolidation; offline gain

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1. Introduction

Learning a new motor skill requires a number of repetitions to implement an optimal adaptation and a stable performance. Additional gain in performance may be achieved when the practice is spaced by intervals of rest [1–3]. This benefit from spaced training—termed offline gain—is associated with the process of memory consolidation developed during the intervals between training sessions [4–6]. In fact, after practice has ended, memory consolidation may be corrupted by interferences induced, for example, by other tasks [7] or molecular synthesis inhibition [8]. Regarding motor skills, between-session intervals of 4–6 h prevent interferences and the memory will be properly consolidated [4,9,10].

As the simple passage of time is an important factor for memory consolidation, the amount of practice engaged before the pause may be crucial to trigger memory processing and the associated offline enhancements. In fact, the consolidation of a memory trace depends on the number of repetitions needed to obtain a relatively stable skill representation. This view is supported by Hauptmann, Reinhart, Brandt, & Karni [11] who used the repetition priming effects to demonstrate that offline gain may be induced when the amount of training was sufficient to achieve a stabilization of the performance.

The majority of studies conducted in the area of spaced learning adopt training paradigms where the performance stabilizes after a relatively low number of repetitions. Thus, the most common outcome in the relevant literature is that the offline enhancement appears early, after the first session of training. However, many everyday motor skills and sport activities require extensive practice, with multiple training sessions before the performance stabilizes. In these cases, the benefits from spaced training may be delayed over the course of the learning period.

In the current paper, we tested the presence of this delay using a precision throwing task that required an elevated number of repetitions to acquire a stable performance. This choice was based on the results reported in our previous work [12] where changes in performance of a precision underarm throwing task were studied over two sessions of practice, followed by a retention test. We showed that the rate of performance change was constant during the first session and stabilized during the second, after a pause of 40 min. Here, we adopted the same paradigm but four training sessions and two groups with practice spaced by 40 min and 1 day were compared. Considering the findings of our previous work [12], if the offline gain was triggered by the amount of practice associated with the performance stabilization, the benefits from spaced learning should be observed starting from the third session and for the group with longer intervals.

2. Materials and Methods

2.1. Participants

We enrolled 16 healthy volunteers (eight women and eight men; age (years), 26.5 ± 3.6; height (cm), 167.7 ± 9.8; weight (kg), 68 ± 13.6) devoid of any experience in precision throwing. The Ethics Committee of the University of Catania approved the study and the volunteers signed an informed consent. All procedures were conducted according to the Declaration of Helsinki.

2.2. Apparatus and Procedures

Experimental procedures were conducted as in Valle et al. [12]. In summary, the participants used their dominant hand to make underarm throws of tennis balls towards a circular target placed on the floor, at the centre of a platform (Figure 1a). Throwing position was 3.42 m away from the target, with the subjects' feet constrained in a parallel configuration.

Each participant performed 1020 throws equally divided over four sessions of training (S1, S2, S3, S4; Figure 1b). Each session consisted of 255 throws divided into 17 blocks of 15 throws, with inter-block pauses of about 2 minutes. Four men and four women were randomly assigned to one of two groups: One group performed the training sessions with breaks of 40 min between the sessions (40-min group), whereas the other group spaced the practice sessions with intervals of 1 day (1-day group). After 15 days from the S4, both groups executed one additional session of 255 throws to test long-term memory retention (RET).

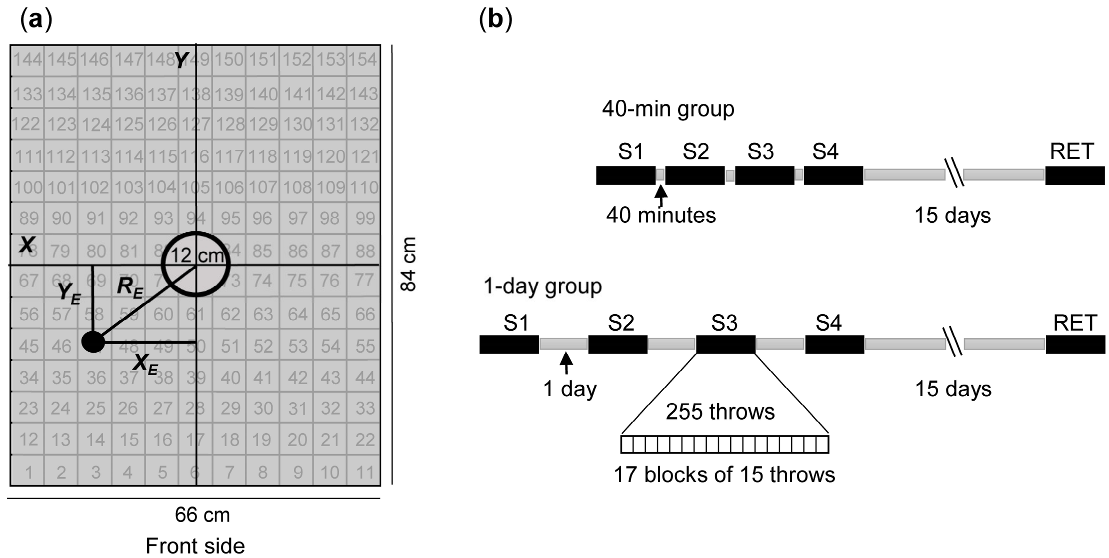

Figure 1. Experimental set-up. (**a**) The target for the underarm throws was marked on a platform placed on the ground. Numbers printed on the platform identified the point of the ball impact. Throwing accuracy was determined by computing the error from the target centre (Radial error, R_E), along the medial-lateral axis (X_E) and along the anterior-posterior axis (Y_E, throwing axis). (**b**) The structure of the learning protocol consisted of four training sessions (S1, S2, S3, S4) and a retention session (RET) performed 15 days after the end of the training. Two groups experienced an equivalent number of total trials, but the training was spaced by 40 min for one group and by 1 day for the other group.

2.3. Measurements

One member of the research team wrote down the number on the platform corresponding to the point of ball impact (Figure 1a). Thereafter, the numbers collected in each session were transformed into Cartesian coordinates with the origin at the centre of the target. The distance between each point and the centre of the target—termed radial error (R_E)—was obtained as follows:

$$R_E = \sqrt{X_E^2 + Y_E^2}, \quad (1)$$

where, X_E represents the error along the medial-lateral axis (parallel to the front side) and Y_E the error along the anterior-posterior axis (aligned to the throwing axis).

2.4. Statistical Analysis

Preliminary power analysis was performed to establish an appropriate sample size. The level of power was set to 0.9 and the other input parameters for the sample size computation were based on the data from our previous paper [12]. Partial eta squared (η^2_p) was used to estimate the sample size for the analysis of variance (ANOVA) with repeated measures and within-between interactions, obtaining a total sample size of eight participants for the $\eta^2_p = 0.3$. For *t*-test comparisons, using means and variances observed previously [12], a sample size of seven participants for each group was obtained. Thus, eight participants for each group were considered a sufficient quantity for the results to be meaningful.

The measurements of consecutive blocks of 15 trials were averaged, obtaining a total of 17 blocks for the session. Single sessions were represented by the average over the 17 blocks. This procedure was applied to each subject and grand averages over the subjects were computed for the statistical analysis and graphic illustrations. Tests for normality (Shapiro-Wilk test) and for equality of sample variances (Levene's test) were performed to provide the basis for using parametric statistics on small samples.

The data were analysed with a three-way repeated measure ANOVA (Greenhouse-Geiser correction), with the group as the between-subjects factor, and session, block or direction as within-subject factors. Interaction factors were also evaluated. A series of unpaired *t*-tests were used for group comparison at each session. The level of significance was set at $\alpha < 0.05$ for all the statistical tests. The magnitude of statistical outcomes was evaluated computing the effect sizes based on η^2_p for the ANOVA and on Cohen's *d* index for the *t*-test.

An additional analysis was conducted to determine the contribution of the directional components to the primary outcome. To this end, we used the following multivariate linear regression model:

$$R_E = \beta_0 + \beta_1 \cdot X_E + \beta_2 \cdot Y_E + \varepsilon, \tag{2}$$

where R_E represents the dependent variable, X_E and Y_E the independent variables, the terms β_0–β_2 the regression coefficients and ε the residual error. To evaluate the specific influence of each of the two independent variables on R_E, the coefficient of determination (R^2) and the partial coefficient of determination (r^2) were calculated by the following equation:

$$r^2 = (RSSp - RSSt)/RSSp, \tag{3}$$

where r^2 represents the fraction of the explained variance that was not accounted for by other predictors, $RSSp$ is the residual sum of squares for the model with all but the single predictor of interest, and $RSSt$ is the residual sum of squares for the model with all predictors.

Sample size and effect size calculations were carried out using G-power software [13] version 3.1.9.2. Statistical analysis and data processing were performed using IBM SPSS, version 25 (SPS S.r.l., Bologna, Italy).

3. Results

3.1. Overall Effect of Spaced Practice on Learning and Memory Retention

The two groups exhibited a significant reduction in R_E (upper graph in Figure 2) over the training sessions ($F_{3,42} = 31.607$; $p < 0.001$; $\eta^2_p = 0.69$), but no significant differences were detected between the groups ($F_{1,14} = 0.003$; $p = 0.956$). However, passing from S1 to S2 the error decrement was larger in the 40-min group than in the other group, while the opposite occurred passing from the S2 to the following sessions, with the 1-day group showing a better performance than the 40-min group. This behaviour produced a significant interaction between the group and session over the four training sessions ($F_{3,42} = 2.823$; $p = 0.050$; $\eta^2_p = 0.17$). When the RET was included in the model, the main effect of the session was comparable with the level of significance detected for the training sessions ($F_{4,56} = 28.151$; $p < 0.001$; $\eta^2_p = 0.67$), but the effect of the interaction between the group and session increased ($F_{4,56} = 3.515$; $p = 0.013$; $\eta^2_p = 0.20$). The statistical comparison at each of the five sessions revealed that significant differences between the groups were detected for the S2 ($t_{32} = 2.710$; $p = 0.011$; $d = 0.929$), S4 ($t_{32} = 2.068$; $p = 0.047$; $d = 0.709$) and RET ($t_{32} = 3.831$; $p < 0.001$; $d = 1.314$).

In summary, the benefits from the spaced practice were delayed over the learning sessions, with significant performance improvements at the end of training and during the memory retention test.

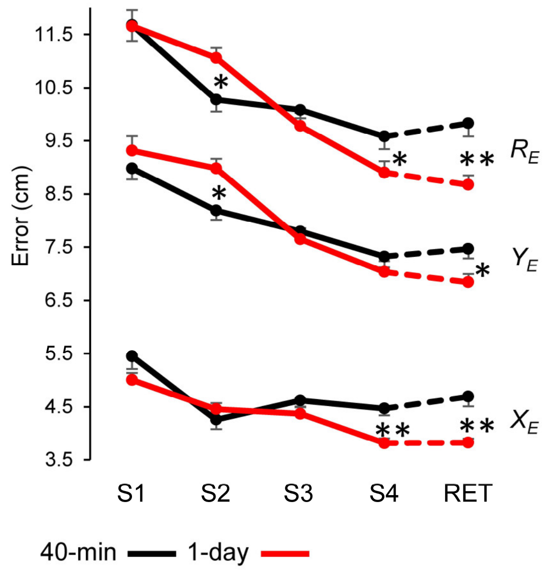

Figure 2. Learning time course over training and retention sessions. Changes in performance are represented as radial error (R_E), medial-lateral error (X_E) and anterior-posterior error (Y_E, throwing axis). Each point represents the grand average ± standard error over the subjects calculated for session 1–4 (S1, S2, S3, S4) and retention session (RET) and for each group (40-min group, black lines; 1-day group, red lines). * $p < 0.05$; ** $p < 0.01$.

3.2. Contribution of Directional Components on the Performance

When the directional components of throwing were included in the three-way ANOVA with session and group, a main effect of direction was observed ($F_{1,14}$ = 180,373; $p < 0.001$; $\eta^2_p = 0.93$), with the error along the axis of throwing greater than along the medial-lateral axis (Y_E and X_E in the Figure 2).There was a significant interaction between session and direction ($F_{4,56}$ = 11,884; $p < 0.001$; η^2_p = 0.46), indicating a different rate of improvement between the directions, over the sessions. As reported for the R_E, a main effect of session was observed also for Y_E ($F_{4,56}$ = 31.070; $p < 0.001$; η^2_p = 0.69) and X_E ($F_{4,56}$ = 8.652; $p < 0.001$; η^2_p = 0.38). However, the interaction between group and session was significant for Y_E ($F_{4,56}$ = 3.073; p = 0.023; η^2_p = 0.18), but not for X_E ($F_{4,56}$ = 1.964; p = 0.113). Although there was no significant interaction between group and session for X_E, the comparison between the groups at each session shows that the differences at the S4 and RET were larger for X_E (S4: t_{32} = 4.147; $p < 0.001$; d = 1.422; RET: t_{32} = 4.388; $p < 0.001$; d = 1.505) than Y_E (S4: t_{32} = 1.024; p = 0.314; RET: t_{32} = 2.630; p = 0.013; d = 0.902). Moreover, the contribution of the Y_E and X_E to the R_E changes, assessed by computing the partial coefficient of determination as Equation (3), were similar for the 40-min group (R^2 = 0.99; r^2 = 0.94 for X_E; r^2 = 0.98 for Y_E) and the 1-day group (R^2 = 0.99; r^2 = 0.84 for X_E; r^2 = 0.99 for Y_E).

These results suggest that the observed skill improvements did not depend only on the changes in performance along the throwing axis, but both directions were adjusted to reduce the error and produce the offline gain.

3.3. Within-Session Changes Associated with Spaced Practice

Figure 3 illustrates block-by-block variations in the R_E within each session. There was a main effect of block ($F_{16,224}$ = 11.7117; $p < 0.001$; η^2_p = 0.46), with most of the changes occurring during S1 and in the first blocks of the following sessions: The performance progressively improved in the S1, but an initial decrement was observed from the S2 to the RET. The amplitude of the initial decrement was similar over the sessions and between the groups. In fact, comparing the last and the first block of consecutive sessions using an ANOVA model including session and group, there was a main effect of block ($F_{1,28}$ = 26.621; $p < 0.001$; η^2_p = 0.49), but no significant differences in the interaction factors were found. However, important differences were detected between the groups: While during the

S2, the initial decrement was followed by a stabilized performance for both groups, from the S3 to the RET, the 1-day group showed a rapid performance improvement after the initial decrement. In fact, considering the last three sessions, there was a significant interaction of group, session and block ($F_{32,448} = 1.612$; $p = 0.020$; $\eta^2_p = 0.10$). Overall, the offline gain may be associated with a fast within-session improvement, whereas the initial performance decrement is independent from the learning period and from the beneficial effects of the spaced training.

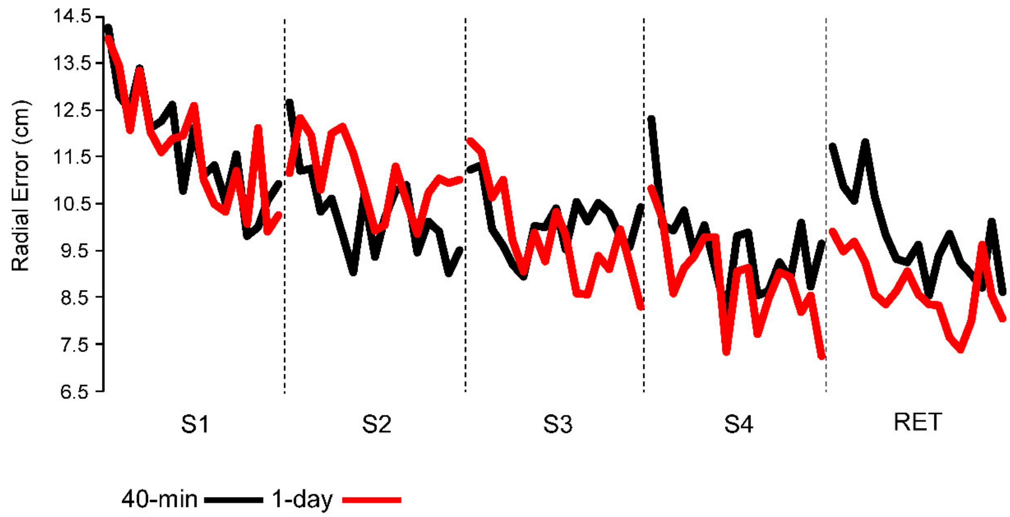

Figure 3. Changes in radial error (R_E) within the sessions. The performance within single session is represented by 17 data points, each summarizing the grand average computed over eight blocks, one for each participant (one block = 15 throws). Abbreviations and labels are the same as in Figure 2.

4. Discussion

The current study shows that benefits from spaced training are delayed when learning a precision throwing task. We also found that both directional components contributed to the error correction improvements and that an initial decrement in performance occurred within the sessions.

4.1. Amount of Practice and Offline Gain

The results reported in this paper indicate that the offline gain may be triggered when the amount of practice ensures a relatively stable outcome. In fact, the 1-day group exhibited a gain in performance during the S3, after a first stabilization occurred over the S2. The beneficial effects of the spaced learning are retained after 15 days from the end of training. This delay in the offline enhancement is in line with the idea that spaced learning promotes a long-term strengthening of the memory traces when the performance stabilizes.

The possibility that a saturated level of performance triggers the benefits from spaced practice was suggested by Hauptmann et al. [11] in regard to the repetition priming effects. Our results on a throwing task combined with previous findings on balancing [14] and visuomotor rotation [15] extend this scheme to the motor domain and suggest that the number of repetitions to achieve a stable performance may depend on the type of task. For tasks requiring a relatively low number of sensory and motor components—such as finger tapping or reaction time skills—the performance may stabilize during the first training session. In the case of more complex tasks, a high number of repetitions may be required to obtain a stable performance, with the consequence of a delay in the appearance of the offline gain. Generally, increases in task complexity are considered critical for the production of benefits from spaced practice [16]. However, possible confusions may arise when the level of practice is not controlled. If, in the current study, we had considered only the first two sessions, we would have concluded that the lack of benefits depended on the task complexity rather than on the limited amount of practice. Our data strongly suggest that misinterpretations about the effects of the spaced training on complex tasks may be avoided by considering the level of practice necessary to stabilize the performance and the associated memory traces.

Delaying the offline gain might serve to exploit the optimization processes following the skill stabilization. Many studies indicate that motor learning is a composite process with a number of components developed over the practice time, as the practice continues [3,17,18]. For example, several authors report that accuracy improvement and strategy optimization may be separate processes. [19–21]. In our previous paper on learning precision throwing [12], we demonstrated that the complexity associated with the ball release parameters was optimized after a first accuracy stabilization. Similarly, when studying the spaced learning during balancing [14], some parameters associated with the structure of the movement strategy showed a delay in the offline gain. Moreover, the association between offline gain and movement optimization may also be supported by the parallel changes observed between the R_E and the error along the two directional components. In fact, this may be considered a signal representing the optimization of the coordination across limb joints, as the movements along the medial-lateral axis mainly depend on the shoulder joint, while the throwing axis is controlled by elbow and wrist rotations.

Although the benefits from spaced learning may be associated with the simple passage of time, periods of sleep might have played a role in the performance enhancement observed for the 1-day group. Although our experimental design did not allow to separate the effects of waking and sleeping intervals on the offline gain, the data suggest that one night of sleep was ineffective in promoting enhancements in performance when a relatively low level of practice was implemented.

4.2. Initial Decrement of the Performance within the Sessions

A recurrent initial decrement in the performance, with respect to the end of the prior session, was detected from S2. The size of this pattern of changes—termed warm-up [3]—was similar for both groups, indicating that offline gain is not influenced by this temporary decrement in performance.

The most direct explanation for these within-session changes is that some information may have been lost during the pause, producing a delay in restoring the acquired skill. However, recent studies suggest that when the practice restarted after a pause, sensory feedback and motor output need to be recalibrated to take into account body and environmental changes [3,22,23]. This may explain the independent timing evolution of the warm-up and offline gain [3]. In fact, the adaptive calibration does not need information derived from the offline processes, but it uses current sensory feedback from external context and internal biomechanical status.

It is possible that the warm-up appears in tasks requiring high accuracy, as in the case of precision throwing. For example, warm-up decrement was associated with the high accuracy observed in skilled basketball players performing set shots at the foul line [24]. In this case, the warm-up may serve for fine-tuning the level of precision, to consider even slight contextual changes. This idea is in accord to the simulation data reported by Ajemian et al. [22], that confirms the key role of the warm-up in realizing precision motor skills.

5. Conclusions

When learning a new motor task requires multiple sessions of practice, benefits from spaced training may delay until the practice produces a stable performance. This scheme, observed here for a precision throwing task, may be a common feature among motor skills requiring actions with high accuracy. In these cases, a performance decrement at the starting of each session, may be a physiological process aimed to recalibrate the level of precision to the changes in the body and environmental context.

The results reported in the current paper may have practical implications for the optimization of training distribution schedules. Controlling for the performance stabilization permits to establish the appropriate amount of practice required to trigger the benefits from spaced training. In addition, when performing a throwing task in the sagittal plane, it is important to consider also the movements on the frontal plane, as both planes of movement contribute to the gain in performance.

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