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Contributions of open-loop and closed-loop control in a continuous tracking task differ depending on attentional demands during practice

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A B S T R A C T

Improving tracking performance requires numerous adjustments in the motor system, including peripheral muscle functions and central motor commands. These commands can rely on sensory feedback processing during tracking, i.e., closed-loop control. In the case of repeated tracking sequences, these commands can rely on an inner representation of the target trajectory to optimize pre-planning, i.e., open-loop control. Implicit learning in a continuous tracking task with repeated sequences proves the availability of an inner target representation, which emerges by learning task regularities, even without explicit knowledge. We hypothesize that the actual use of open-loop or closed-loop control is influenced by the demand for attention. Specifically, we suggest that closed-loop control and its development during practice need attentional resources, whereas open-loop control can work and evolve in a more automatic way without attentional demands. To test this, we investigated motor-control strategies when extensively practicing a continuous compensatory force-tracking task using isometric leg muscle activation, either as a single-motor task or as a motor-cognitive dual task. After training, we found evidence for predominantly closed-loop control in the single-task training group and for open-loop control in the dual-task training group. In particular, we ascertained dual-task motor costs and a weakly developed implicit knowledge of task regularities in the single-task training group. In contrast, in the dual-task training group dual-task motor costs disappeared, while implicit learning was clearly observed. We conclude that motor-cognitive dual-task training may boost implicit motor learning, without necessarily impeding concurrent improvement in the cognitive task.

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1. Introduction

Tracking tasks require participants to follow a pre-specified dynamic template as closely as possible. There are two common types of tracking tasks: pursuit tracking and compensatory tracking. In pursuit tracking, the template is represented by a moving target that

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participants must follow with a cursor. In compensatory tracking, participants have to minimize the effects of a changing offset by counter-steering in order to keep the cursor stationary at a defined position. An integrated measure of either the coherence or the deviation between the produced behavior and the template is used to quantify tracking performance. Typically, practice improves performance until a performance plateau is reached. Two mutually dependent mechanisms can be identified that contribute to learning (see for a review Walter, Günther, Haeufle, & Schmitt, 2021). Firstly, improvements can be associated with effects in peripheral activity, such as optimized use of energy for muscle contraction after adapting to task requirements. Secondly, improvements may result from more efficient information processing, allowing for better use of sensory feedback to quickly eliminate deviations between the tracking template and own behavior using closed-loop control. The degree of accuracy achieved by such closed-loop control depends on the coherence between time delays, feedback gains, and the size and variability of sensory and motor errors. Therefore, performance increments depend on optimizing the fit of these parameters during practice. Furthermore, if the template includes regular, i.e., predictable components, acquired knowledge about these regularities may be used in anticipating upcoming template changes in an open-loop fashion. In order to do so, an internal representation of the template capturing its relevant features has to be built up.

During tracking, both closed-loop and open-loop control contribute to moment-to-moment control. The degree to which each of them is utilized depends partly on the availability of certain central cognitive processing resources, like attentional resources. In particular, attentional resources are required for consciously controlled processing and adjusting to visually presented deviations from target during tracking. However, as the capacities of processing resources are limited (Kahneman, 1973), the availability of a particular control protocol is determined by the limits of the individual resource capacities and the already occupied amount of resources. Furthermore, certain attentional resources are also associated with the capacity of the working memory resources (Ahmed & de Fockert, 2012). Consequently, central processing resources may degrade task performance if processing requirements of a given task exceed a certain limit. However, this lack of resources may be less relevant in case of automatic processing, assuming that automatic control does not underlie resource limitation (see for a review Oberauer, 2019).

In motor control, both mechanisms, open-loop and closed-loop, may include more or less controlled or automatic processing. This concerns ongoing closed-loop corrections for eliminating momentary deviations (e.g., in a walking task: Bucklin, Wu, Brown, & Gordon, 2019; in a pointing task: Priot, Revol, Sillan, Prablanc, & Gaveau, 2020) as well as running off an existing inner representation of a template (e.g., in a juggling task: Schaal, Atkeson, & Sternad, 1996; in a finger-tapping task: Zhang, Jiang, Yuan, & Zheng, 2021) ('inner representation of the template' will be called 'inner template' in the following). In this context, updating of feedback gains is a fundamental process of our motor control system, which should be automatic, at least at lower hierarchical levels of control, requiring almost no general central processing resources. Evidence for this assumption comes from studies in which the synchronization of feedback-controlled motor behavior (with and without divided attention) with the sensorimotor relevant beta frequency band of the electroencephalogram was investigated (Kristeva-Feige, Fritsch, Timmer, & Lücking, 2002; Safri, Murayama, Hayashida, & Igasaki, 2007). Yet, this might be different for processes involved in the establishment of an inner template. In order to detect regularities, information needs to be integrated over several trials, which may involve general memory processes, like working memory processes, internal verbalizations or visualizations. This assumption is in line with other observations in cognitive psychological paradigms like the sequence-priming paradigm. At the beginning of learning, memory demanding processes are heavily taxed. However, with continued practice, the skill becomes more automated and less dependent on attentional resources (Spruyt, Gast, & Moors, 2011). Yet, there is also evidence for the contrary view that template generation and use may also occur in a more or less automated fashion. It is supported by the observation that tracking performance of a regular segment can be improved without explicit knowledge or awareness that there was any regularity at all. This robust empirical observation is known as 'implicit learning' (for reviews see: Reber, 2013, and Seger, 1994). The processes underlying implicit learning operate very effectively in generating an inner template without awareness, and trying to deliberately pay attention to these processes may even be detrimental to learning (Wulf & Lewthwaite, 2016). Indeed, an additional process drawing attention away from an intentional search for task regularities may promote an undisturbed operation of the implicit learning mechanisms (Beilock, Carr, MacMahon, & Starkes, 2002). Following this rationale, we argue that learning a tracking task concurrently with a demanding additional task might boost implicit learning. Note, this expectation only relates to the processes involved in learning, i.e., practice related changes in performance. Momentary tracking performance during practice may nevertheless decrease if a second task has to be performed in parallel, as has been observed in implicit motor learning studies (golf putting: Masters, 1992; Maxwell, Masters, & Eves, 2000). Assuming the system is more challenged while performing two tasks concurrently, this might require both a greater flexibility in the acute use of the motor control components and implicit learning. That is, participants would have to repeatedly switch between closed-loop and open-loop control during tracking to be able to process the additional task as well. Nevertheless, participants might benefit from this situation in the long run, particularly from the establishment of an inner template by processes of implicit learning. Of course, implicit learning is also possible under motor single-task condition, i.e., when closed-loop control is undisturbed and fully available. However, learning rates and the quality of open-loop and closed-loop components may differ depending on the learning conditions, particularly single-task vs. dual-task training. In the following paragraphs, we will elaborate on where these differences might become visible and how they can actually be quantified.

1.1. Disentangling the effects of open-loop and closed-loop control components in the tracking task

Due to the strong mutual dependencies between open-loop and closed-loop control processes, it is challenging to identify the specific contribution of each of these control processes. Furthermore, if we purely look at a single behavioral measure, it is difficult to determine the extent to which, for example, an observed reduction of errors is caused by a stricter closed-loop control or by a better open-loop anticipatory control based on a learned template. Several experimental techniques have been pursued to disentangle closed-loop and open-loop control. We will have a closer look at five of these techniques in the following: i) withdrawal of concurrent feedback, ii) comparing learning benefits between predictable and unpredictable templates, iii) analyzing temporal delays, iv) analyzing frequency components of the response, and v) contrasting distance based and correlational measures of performance. The first two of these techniques (i and ii) rely on manipulations of an independent variable, the latter three (iii to v) comprise analyses of specific dependent variables.

1.1.1. Withdrawal of concurrent feedback

Closed-loop control indispensably relies on the availability of online feedback about the current status of the own movement relative to the current target. Consequently, withdrawing such information would completely disrupt any closed-loop contribution to tracking performance, rendering tracking performance exclusively to open-loop control. Along this line of reasoning, Davidson, Jones, Sirisena, and Andreae (2000) provided evidence for a strong contribution of closed-loop control in a tracking task. They showed that withdrawal of visual online information about the own movement severely reduced spatial accuracy in a pursuit tracking task. However, there were clear indications that participants somehow still reproduced regularities in the tracking task to some extent, demonstrating an open-loop control component in tracking performance.

1.1.2. Comparison of learning benefits between predictable and unpredictable templates

Anticipatory open-loop control requires prior knowledge on how the template will evolve in the future. Knowledge about regularities in the tracking template is accumulated during practice. At least some of these regularities are then reflected in an inner template stored in memory. This inner template is then used as a basis for open-loop control in subsequent trials.

A research line originating from an early work by Pew (1974) has studied how such an inner template is built up during practice. Typical for these experiments is that a sinusoidal tracking path is divided into three segments of similar duration. One of the segments is repeated in each trial, the other two segments change randomly from trial to trial. Independent of the position of the repeated segment (i.e., between, before or after random segments), performance in the repeated segment increased more throughout practice than in the random segments (Künzell, Sießmeier, & Ewolds, 2016; Zhu et al., 2014), indicating the formation of an inner template for the repeated segment (de Oliveira, Raab, Hegele, & Schorer, 2017; Ewolds, Broeker, de Oliveira, Raab, & Künzell, 2021; Ewolds, Bröker, de Oliveira, Raab, & Künzell, 2017). All these studies contrast closed-loop and open-loop control processes by comparing the tracking of a random segment, which almost exclusively relies on closed-loop control, with a repeated segment, which relies on both closed-loop and open-loop control.

1.1.3. Analyzing temporal delays

If an inner template is available that reflects the temporal characteristics of the tracking template with sufficient accuracy, the open-loop control component can anticipatorily move the end-effector in the correct direction without any temporal delay. This is different for the closed-loop component. Due to the limitations in processing speed, any changes that exclusively rely on feedback processing can only be effected with a certain temporal delay (Boyd & Winstein, 2004). Therefore, any adjustments made by the closed-loop system should trail the changes in the external template by a more or less fixed delay. When tracking behavior is strongly governed by such delayed closed-loop adjustments, correlation between actual cursor value and target value should increase when the actual cursor trajectory is time-shifted by the duration of the feedback delay. On the other hand, when the process is strongly governed by no-delay open-loop control, correlation should be highest with zero time-lag. Accordingly, analyzing the effect of time-shifting on the resulting correlation coefficients might reveal insights into the relative importance of closed-loop and open-loop control for tracking performance.

1.1.4. Analyzing frequency components of the response

Related to the previous point, closed-loop control may also be revealed by effects in the frequency domain. Specifically, this means that if a deviation from the target is detected it will be answered by a compensatory activity in order to reduce the error. After each correction, a short waiting-time interval will follow to see whether this correction was successful, and only then may the next potentially corrective activity be initiated (Miall, 1996). This intermittent control should then show up as increased power in frequency components related to typical delays of human feedback loops (Miall & Jackson, 2006). In contrast, we assume that open-loop control is continuous rather than intermittent and hence unaffected by such oscillations. Accordingly, power accumulation in particular frequency components may be interpreted as an indication of stronger involvement of closed-loop control.

1.1.5. Contrasting distance based and correlational measures of performance

Revisiting technique i (see Section 1.1.1), Lang, Gapenne, and Rovira (2011) found that removing feedback of the cursor position resulted in significantly reduced spatial accuracy, i.e., increased distance between the cursor and the target position, often expressed by larger root-mean-square errors (RMSE). The extremely poor accuracy in the occlusion condition made the detection of an implicitly learned open-loop component via RMSE impossible. However, Lang and colleagues still found signs of implicit learning when looking at a coherence measure, i.e., the time-locked correlation between cursor and target position (called SIMI as shortcut for *simi*larity in the following). SIMI was higher in the repeated segment compared to the random segments. Irrespective of the fact that actual movement amplitudes undershoot the required amplitude, this measure still captures contingencies in the progression of values over time. Compared to the more spatial deviation-dependent measure RMSE, SIMI more strongly reflects coherence in the temporal evolution of events and thus seems to be more sensitive to learning effects related to open-loop control (Yang, Wan, Nan, Zhu, & Hu, 2017).

In the following, we will try to illustrate our assumptions regarding higher and lower sensitivity of RMSE and SIMI in four characteristic scenarios (see Fig. 1). We inferred that as soon as the closed-loop component is more strongly involved in tracking, the SIMI measure is also positively affected to some extent (see Fig. 1 C and D). Only following an inner template indicated by a high SIMI and less pronounced spatial accuracy (relatively high RMSE) enables to distinguish between the motor-control mechanisms (see Fig. 1 B).

1.2. The current investigation: Effects of an additional cognitive task on tracking control and learning

Tracking tasks can count as a prototypical situation where closed-loop control plays an important role for successful performance (Davidson et al., 2000; Davidson, Jones, Andreae, & Sirisena, 2002). Further, it has been widely studied how tracking performance is affected by additional concurrent tasks (de Oliveira et al., 2017; Ewolds et al., 2021; Lang et al., 2011) and how regular components of a tracking task are learned and then used to improve performance by adding open-loop components to the ongoing tracking control (Vidoni, McCarley, Edwards, & Boyd, 2009; Wulf & Schmidt, 1997). However, studies looking at how the use of these open-loop components are affected under dual-task conditions are rare. As an example, Ewolds et al. (2017) reported no motor costs reflected in RMSEs after dual-task training (manual pursuit tracking with an acoustic Go/NoGo task), whereas single-task training did not eliminate motor costs. Nevertheless, implicit learning was found in participants of both training regimes. In our study, we aimed to get a deeper understanding of whether a demanding additional task hampers the learning progress (Beilock et al., 2002) or whether, due to blocking the influence of potentially harmful attentional processes, it even improves learning. In order to be able to dissociate effects on actual tracking control and learning processes, we relied on several of the techniques mentioned above (i.e., for the independent variables: ii, and for the dependent variables: iv and v), allowing us to quantify contributions of closed-loop and open-loop components separately.

In our study, we used a compensatory tracking task, where participants had to align a cursor with a target line by applying pressure to a force plate in a leg press machine. During training, we manipulated attention to the tracking task by either allowing full attention or distracting attention by adding a secondary task. To this end, we incorporated a single-task training (STT) group and a motor-cognitive dual-task training (DTT) group and quantified group differences in implicit learning. Implicit knowledge was deduced by comparing performance in the repeated segment with the averaged performances in the adjacent segments, which changed randomly from trial to trial. In order to receive a more fine-grained picture of individual control behavior, we used an isometric force-tracking task. The registered forces reflect motor control output more directly than the kinematic trajectory of an effector, which actually needs to be moved. When a considerable mass including body parts (e.g., arm and hand) has to be moved, this would necessarily comprise a low-pass filter due to inertial damping (Krylow & Rymer, 1997). Therefore, the signal from an isometric task is better suited for the temporal analyses according to the Sections 1.1.4 and 1.1.5. Furthermore, we were interested in the robustness of implicit learning. To investigate this, we not only tested the repeated segment effect associated with training, but also tested segment effects in an additional catch-trial block. In the catch-trial block, we substituted the repeated segment used during practice by a different segment, which was then also repeated from trial to trial within this block. This allowed us to determine the degree to which acquired implicit knowledge is

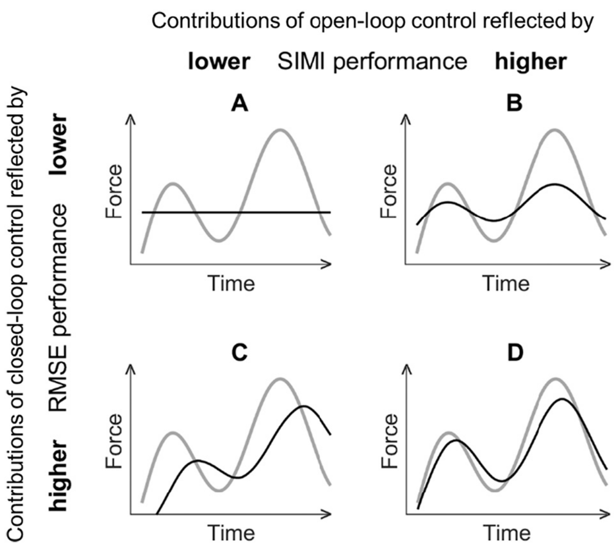

Fig. 1. Combinations of closed-loop control and open-loop control reflected by higher (i.e., better) or lower performance in RMSE and in SIMI. Thick grey lines indicate the template and thin black lines represent possible tracking curves. Please note, RMSE relies on the absolute distance of the force values, while SIMI quantifies time-locked coherence via correlation. (A) When both parameters show low performance, participants do not sufficiently execute the instruction. (B) When predominantly using open-loop control, SIMI would show high accuracy while there still might be a spatial error. (C) When following the instruction by predominant closed-loop control, spatial accuracy will be rather high, while SIMI is reduced due to the temporal delay for the feedback-control loop. (D) A mixture of closed-loop control and open-loop control should result in high spatial accuracy and high SIMI value, which should only be observed as a training effect.

susceptible to short-term interference by new regularities in the task.

Given limited central processing resources, we also expected an acute drop in performance under dual-task conditions compared to single tracking-task conditions. A drop in performance on at least one of the tasks components in a dual-task indicates interference of competitively used central resources (e.g., attentional resources) when concurrently processing two tasks (see for a review Wickens, 2021). However, we were not sure how learning would be affected by the secondary task. If implicit learning benefits from drawing away attention, we should measure beneficial effects of a secondary task after learning. Given previous studies, the SIMI measure should be more capable in detecting the use of an inner template, whereas RMSE is more sensitive to closed-loop control performance.

2. Materials and methods

2.1. Participants

Based on a power analysis (G*Power, version 3.1.9.7; Faul, Erdfelder, Buchner, & Lang, 2009), we expected a sample size of 28 participants in order to reach a power of $\geq$0.95 with an α-level of 0.05 in a repeated measures ANOVA with mixed design, assuming a medium effect size *f* of 0.25 and a correlation between measurements of 0.70. In total, 32 young and self-declared healthy people from the local student population were recruited to participate in the pre-post training study, including a late follow-up measurement. However, four participants (i.e., one out of 15 in the STT group and three out of 17 in the DTT group) admitted that they did not completely comply with instructions and were therefore excluded from the analyses. The following data refer to the remaining 28 participants included in the different analyses.

Participants were allocated to one of two training groups, stratified by the number of correct responses in the cognitive task during pretest (see Section 2.2 for a description of the cognitive task). Both groups consisted of 14 participants (STT: 10 female and 4 male, mean age $\pm$ SD: 23.8 $\pm$ 3.8 years; DTT: 13 female and 1 male, mean age $\pm$ SD: 23.2 $\pm$ 3.9 years). In order to keep physical demands of the motor task comparable between individuals, we adapted the task requirements to the individual force maximum (F_{max}) (see Section 2.2 for the practice-task description and Fig. 3). We tested for group differences in F_{max} and found both groups were on a comparable level (see Fig. 2), $t(13) = -2.632$, $p = .127$, i.e., 1990 $\pm$ 480 N for the STT group and 2150 $\pm$ 780 N for the DTT group.

All participants gave written consent for participation in this study, which was approved by the local Ethics committee. Participation was compensated by a maximum of 118 €, i.e., 8 € per hour and extra prize money (30, 20 or 10 €) through a lottery, where more tickets could be earned with better test performance.

2.2. Apparatus and tasks

We used a leg-press machine (MW Künzler Sport, Germany) customized to fit a strain gauge (measuring range: $\pm$ 5000 N, biovision, Germany). The data signal was amplified (DMS-amplifier, biovision, Germany) and captured using a data acquisition device (USB-6009, National Instruments, USA) with a sampling frequency of 50 Hz. The recorded data were used to calculate the difference between required and actual force production, in order to provide online feedback by a beamer projection (EPSON, Japan; refresh rate 60 Hz) on the wall in front of the participants at a distance of about 4 m. These data were saved for offline analyses.

The *motor single task* in this study was a continuous compensatory force-tracking task. The required force-tracking template was a sine curve created as proposed by Pew (1974) using 41 sets of parameters, of which 37 were evaluated by Künzell et al. (2016). They showed that implicit learning occurred independent of the curve parameters. Thus, three separate segments were calculated by $f(x) = a_0 + \sum_{n=1}^{6} a_n cos(\mathrm{x}) + b_n sin(\mathrm{x})$, where a_0 to a_6 and b_1 to b_6 were the predefined coefficients and x the time interval, which was of constant duration. Next, we linked the segments by spline interpolated transitions (see Fig. 3). To adapt physical load to the individual, the curve was calculated for 10% of F_{max} and normalized to the range of $\pm$5% of F_{max}. This procedure induced the exploitation of the individual curve range in each of the segments. During motor task execution, deviation from force template in amount and direction was shown by a moving horizontal bar (see Fig. 4 A). When the bar was below the dotted line, force was smaller than required, and vice versa. Participants were instructed to keep the bar as close as possible to the dotted line by adapting force application on the footrest platform.

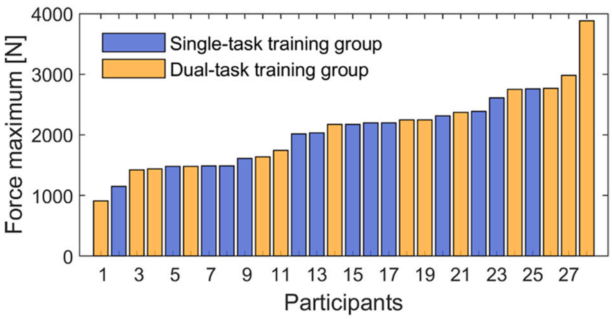

Fig. 2. Sorted individual maximal isometric force production (F_{max}).

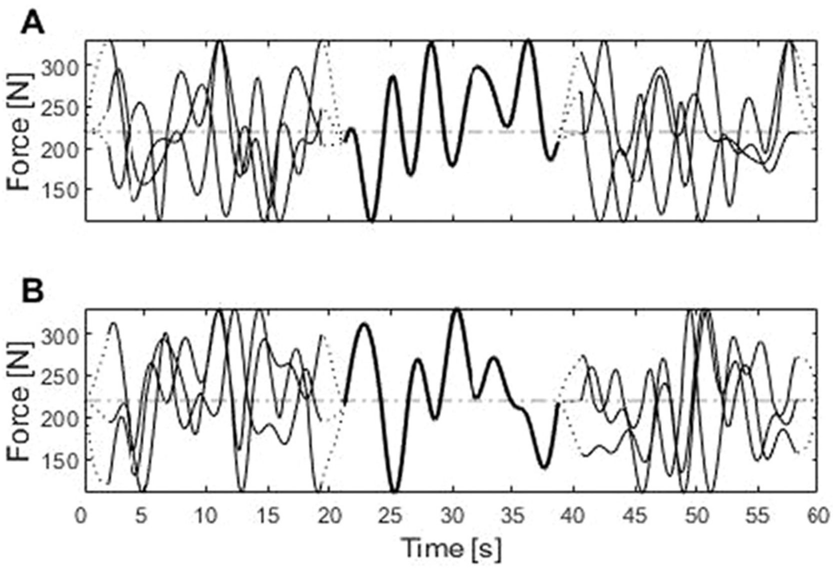

Fig. 3. Exemplary force templates for test trials of a single participant. Each panel depicts three curves over time, meandering around 10% of the maximum force (grey dotted horizontal line). During the first and the last 20 s, random curve templates were used for every trial (black thin lines). During the middle 20 s, the same curve template (black thick line) was used for the tests and training conditions (A) and the catch trials (B) for the tests only. Dotted lines in the beginning and at the end of each 20 s segment represent interpolated sections, which ensure a smooth transition between segments.

In order to be able to test implicit learning, we created two task variants with a repeated middle segment, while the first and last segment randomly changed from trial to trial. In the following, we use the term *practice task* (PT) as a task variant, when the repeated segment was tested (pre-, post-, and retention test) and practiced during training (see Fig. 3 A). The other task variant, the *catch-trial* block included a new repeating middle segment (see Fig. 3 B), which was only used during the three test sessions. Thereby, the catch trials (CT) should indicate interference effects due to the new regularities.

The *dual-task condition* required executing the motor task and an additional cognitive task concurrently, with slightly different cognitive task features in the test versus the training sessions. For the test sessions, the cognitive task was a mental subtraction task which required subtracting a two-digit number from a four-digit number of higher level of complexity; for example, '2345 – 67' demanded two borrows at the 2nd and 3rd position. A task set of 300 tasks was prepared and used for each participant in the same order. The subtraction task was presented within the bar for the motor-task feedback (see Fig. 4 B). This means that ignoring the motor

Fig. 4. Visual representation of the single-motor task (A) and the dual-task (B). The position of the grey bar was controlled by the leg press. Participants were instructed to keep the arrows within the bar as close as possible to the dotted black horizontal lines.

task would not only result in stronger bar movements but also increase up and down movements of the calculation-task representation. Immediately after the participant's verbal response a research assistant pressed a button to display the next calculation-task trial. Participants were asked to verbalize as many correct subtraction solutions as possible within the given time. Additionally, we instructed participants to perform both tasks as accurately as possible.

Training required an alteration to the cognitive task for the DTT group. The cognitive task during training was also a subtraction task, but now we provided different degrees of difficulty in the subtraction task, i.e., the number of borrows varied equally distributed from zero to two. Further, DTT participants self-controlled the amount of calculation tasks by manually responding using a computer mouse. Participants indicated the end of calculation by a mouse click. Then, a computer-generated response appeared stepwise from the 4th to the 1st position in the bar with onset intervals of 750 ms (i.e., overall display time for the result was 3000 ms; see Fig. 5). Participants had to compare their own calculated result with the numbers popping up. In the case of agreement, participants had to do nothing and wait until the next task appeared automatically in the bar. In the case of disagreement, participants had to stop the result display by another mouse click. Immediately after this mouse click, the next task appeared in the bar. Participants were asked to improve both motor and cognitive performance during training.

2.3. Procedure

The entire study included three test days, i.e., pretest, posttest and retention test. Tests were only conducted on days when there

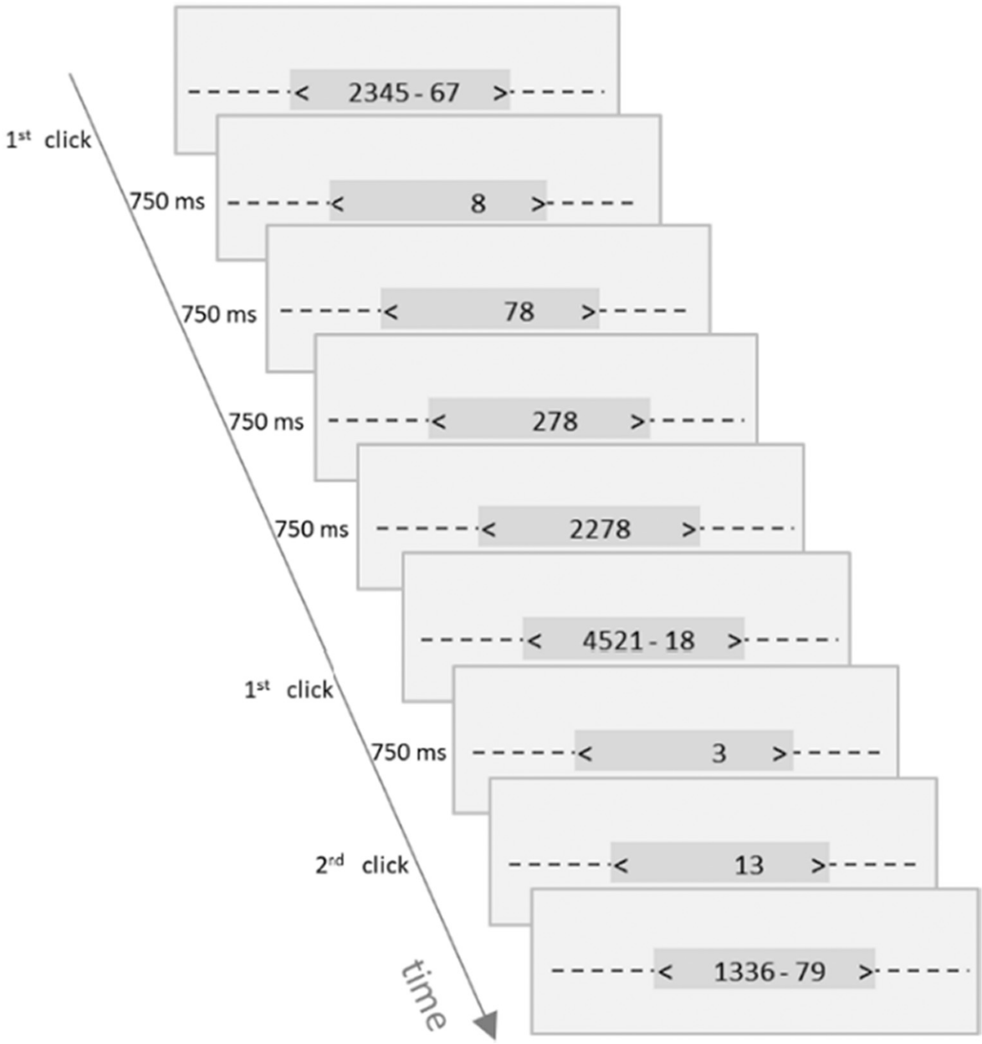

Fig. 5. Cognitive task procedure during dual-task training. The first mouse click (1st click) performed by the participant indicates finishing the calculation phase. Immediately after, a computer-generated result appeared stepwise and had to be compared with the own mental representation of the task solution. When the presented result was identified as wrong, another mouse click (2nd click) was done for presentation interruption. If the presentation was correct, participants were asked to await the next task automatically after the presentation was terminated after 3000 ms, in total.

was no training. Between pretest and posttest, participants completed a minimum of 330 and up to a maximum of 360 training trials. After a posttest they had no further training until the retention test, which took place 10 to 12 weeks after the posttest.

At the beginning of the pretest, the maximum isometric force of the leg extensors was measured over 10 s in a leg-press machine at a knee angle of 100°. The individual sitting position was recorded and used for all testing and training sessions. Then, we tested motor single-task and motor-cognitive dual-task performance within two test blocks. The order of the tests was pseudorandomized and counterbalanced across participants. Each of the blocks included either the not yet practiced repeated segment or the catch-trial segment. Within the blocks, we alternated the motor single-task condition and the dual-task condition. Each condition was performed in three trials and each trial was of 60 s duration. Between trials there were 45 s breaks.

After the pretest, participants started the practice sessions. They had to complete 22 to 24 training days within 5 to 6 weeks. On average, participants in the STT group completed 23.4 ± 0.8 training days and the participants in the DTT group 23.6 ± 0.7 training days. On each training day, participants performed 15 trials of the practice task of 60 s duration, alternated with recovery phases of 60 s duration. Depending on the group assignment, participants practiced either just the motor single task or the dual-task (i.e., tracking and calculating). After each trial, each participant obtained feedback on the motor performance based on RMSE. Perfect performance (i.e., an error of zero) resulted in a value of 100. The larger the RMSE the smaller the performance score, which was calculated using linear regression. DTT participants additionally got feedback on their cognitive performance, which included the number of correct responses and relative accuracy in percentage.

After the training sessions, participants performed the posttest, and eight to 12 weeks later, the retention test (mean ± SD of the retention interval for STT group was 10.9 ± 2.0 weeks, and for DTT group 10.6 ± 1.8 weeks). These test sessions were identical to the pretest except for the removal of the maximum leg force measurement. In the tests, participants did not obtain information about their cognitive, motor and dual-task performance. Blocks and task orders were pseudorandomized across participants and tests. After the retention test, participants were asked to report about characteristics of the practice task, in order to find out if they acquired explicit knowledge of the repeating segment.

2.4. Data preprocessing

Raw force data were filtered using a 2nd order low pass Butterworth filter (cutoff frequency = 3 Hz). For each segment, we calculated the RMSE and SIMI excluding the transition parts of the segments (see Fig. 3). RMSE was the normalized relative deviation from force template [$RMSE\,[\%] = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(template_i - produced\ force_i)^2}/F_{max} \bullet 100$] with n representing the data length of a single segment. SIMI was determined by the *Pearson's* correlation coefficient [$r = \left[\sum_{i=1}^{n}(x_i-\overline{x})(y_i-\overline{y})\right] / \left[\sqrt{\sum_{i=1}^{n}(x_i-\overline{x})^2}\sqrt{\sum_{i=1}^{n}(y_i-\overline{y})^2}\right]$] where x is the template and y is the produced curve for each time point i of segment length n. In order to investigate implicit learning effects in both motor parameters, we compared the repeated segment (RMSE: PT_{repeat}; SIMI: PT_{repeat}) with the average of the two random segments (RMSE: PT_{random}; SIMI: PT_{random}) and with the replaced middle segment (RMSE: CT; SIMI: CT). Cognitive performance was represented by the number of correct responses (CR) and the accuracy rate [$AR\,[\%] = number_{correct}/number_{total} \bullet 100$] for each completed trial.

2.5. Statistical analyses

We used the open-source JASP software (version 0.13.1.0) for inferential statistics and Matlab 2019b (The Mathworks Inc., Nattick, USA) for all other described steps. First, we checked for explicit knowledge as it was an exclusion criterion. In addition, for each individual we had to find out the number of training trials that can be associated with noncompliance with the training instruction, as for example, depicted in Fig. 1 (A). We had to exclude participants with 30 or more inadequate training trials, i.e., with a total of two or more inadequate training days, because we set a priori the minimum number of active training days at 22. Because we could not determine the lower bounds for normal performance a priori, we considered the distribution of both performance measures including the entire trial (i.e., independent of the segments), in which all training trials of all participants were combined. Using a boxplot technique, we determined the critical values for error outliers (see for review: Aguinis, Gottfredson, & Joo, 2013) in RMSE and SIMI indicating deviated performances across all participants. The number of inadequate trials was then quantified for each participant by adding the number of outlier trials in the RMSE measure and the number of outlier trials in the SIMI measure and subtracting the number of combined RMSE and SIMI outlier trials. In case of the exclusion of data sets, we further need to check the power of the remaining sample size and to adjust the α-level if we retain our belief in the null hypothesis.

In the next step, we checked the cognitive data (i.e., CR and AR) for compliance with the instruction. To this end, we used a two-factorial (Test: pretest, posttest, retention) repeated measures ANOVA with mixed design (Group: STT, DTT) to explore test-time-related group differences. Another repeated measures ANOVA was conducted to check training progress in the DTT group. As a last prerequisite we checked whether pretest differences in performance at group level need to be considered when interpreting upcoming behavioral data. Both cognitive performances were tested separately by independent t-tests. For RMSE and for SIMI we calculated two-factorial (Segment: $PT_{repeated}$, CT; Load: single task, dual task) mixed (Group: STT, DTT) repeated measures ANOVAs.

Then, we conducted repeated measures ANOVAs in order to quantify practice effects with respect to implicit learning (Segment: $PT_{repeated}$, PT_{random}) during training (Day: 1, …, 22) in RMSE and in SIMI for each training group, separately. Further ANOVAs tested the within-subjects factors Test (posttest, retention test), Segment ($PT_{repeated}$, PT_{random}, CT) and Load (single task, dual task), and the between-subjects factor Training Group (STT, DTT).

Lastly, we analyzed the relative power of the adaptation frequencies in the tracking task for lower frequencies (i.e., <1 Hz) and for higher frequencies (i.e., 1 to 2.5 Hz) with the higher frequencies mainly reflecting closed-loop control in healthy adults (Miall & Jackson, 2006). We conducted frequency analyses (see Section 1.1.4) using Fast Fourier Transformation and estimated the relative power by calculating the integral for each frequency band relative to the total power estimation of the according segment. We were interested in changes of the relative power contribution in each segment separately across training (i.e., at early training period on days 1 to 3 and at the late training period on days 20 to 22). In order to analyze the differences between the training Groups (STT, DTT) for the Segments (1, 2, 3; i.e., 1st PT_{random}, $PT_{repeated}$, 2nd PT_{random}) and for the six representative training Days (1,2,3,20,21,22) we used another mixed design repeated measures ANOVA. In case of violated sphericity in any of the ANOVAs, Greenhouse-Geisser correction was applied. For all *post-hoc t*-tests we used the Bonferroni correction.

3. Results

3.1. Compliance with motor task instructions

No participants, in either the STT or DTT groups, reported knowledge about task characteristics. Fourteen participants per group were checked for noncompliance during training (see Section 2.5). In total, we detected 1.7% outliers in the RMSE data pool (i.e., trials showed an error larger than 30.15%) and 8.5% outliers in the SIMI data pool (i.e., temporal coherence in the trials was below r = 0.248). We found three participants in the STT group and four participants in the DTT group non-complying with training instructions in at least 30 training trials. Hence, data from 11 participants from the STT group and 10 participants from the DTT group entered further analyses. This data reduction was tested for *post-hoc* power, which reached 0.886. Therefore, we adjusted the α-level to 0.114 in order to reduce the Type-II-error.

3.2. Compliance with the cognitive instructions

We investigated cognitive performance improvement for the training groups over the three test sessions (see Table 1 and Fig. 6). For CR we found a main effect for the factor Test, $F(1.664, 31.616) = 65.190$, $p < .001$, $\eta_p^2 = 0.774$, and a Test × Group interaction, $F(1.664, 31.616) = 15.387$, $p < .001$, $\eta_p^2 = 0.447$. In detail, the STT group improved CR by about 1.5 ± 0.5 from pretest to posttest, $t(10) = 3.022$, $p = .040$, while the DTT group improved CR by 5.4 ± 0.5, $t(9) = 10.511$, $p < .001$. At retention test, there was no significant change compared to posttest in CR for either training group. For AR (see Fig. 6) we only found a main Test effect, $F(1.421, 26.997) = 14.369$, $p < .001$, $\eta_p^2 = 0.431$. Accuracy in the cognitive task improved by about 23.0% (SE: 5.0%) from pre- to posttest, $t(19) = 4.574$, $p < .001$, Cohen's $d = 0.998$, and remained similar at retention test. In addition, the cognitive training improvement for the DTT group was significantly different from zero for both parameters (see Fig. 6): CR, $F(21, 189) = 47.889$, $p < .001$, $\eta_p^2 = 0.842$, and AR, $F(21, 189) = 6.612$, $p < .001$, $\eta_p^2 = 0.424$. Both goups improved cognitive performance. For group STT this can be interpreted as a test repetition effect. Due to the cognitive training, group DTT improved much stronger. Hence, both groups complied with the cognitive training and test instructions.

3.3. Verifying equal performance levels at pretest

We used a t-test to check for differences in cognitive performance between groups at pretest. As shown in Table 1 and Fig. 6, cognitive performance levels were similar in both parameters: CR, $t(19) = -0.064$, $p = .950$, and AR, $t(19) = -0.707$, $p = .488$.

We also checked for performance differences between repeated practice and catch trial segment to make sure that there was no initial difference and quantified the dual-task motor costs. We calculated two-factorial (Segment: $PT_{repeated}$, CT; Load: single task, dual task) mixed (Group: STT, DTT) repeated measures ANOVAs for RMSE and SIMI, separately. There was neither a main effect for the factor Segment in RMSE, $F(1, 19) = 1.188$, $p = .289$, $\eta_p^2 = 0.059$, nor in SIMI, $F(1, 19) = 0.313$, $p = .583$, $\eta_p^2 = 0.016$. Further, there were no significant group-specific differences, both Segment × Group interactions revealed $ps \geq 0.261$. However, we found cognitive Load main effects in RMSE, $F(1, 19) = 18.431$, $p < .001$, $\eta_p^2 = 0.492$, and SIMI, $F(1, 19) = 5.810$, $p = .026$, $\eta_p^2 = 0.234$ (see Table 2). Both groups suffered similarly from the dual-task condition represented by a performance decrement of 2.8% (SE: 0.7%) in RMSE and 0.06 (SE: 0.03) in SIMI, both $ps \geq 0.508$.

Table 1

Averaged accuracy rate (AR) and number of correct responses (CR) per training group at each test session when performing the cognitive task and the tracking task concurrently. Data represent mean values and standard deviations within brackets.

	Pretest		Posttest		Retention	
	STT	DTT	STT	DTT	STT	DTT
Number of correct responses [#]	3.1 (2.3)	3.2 (2.3)	4.6 (2.6)	8.6 (2.5)	5.6 (2.6)	7.9 (2.3)
Accuracy rate [%]	57.6 (25.4)	66.3 (30.6)	74.4 (26.5)	95.5 (4.7)	79.8 (28.2)	91.5 (5.2)

DTT (dual-task training) group: sample size = 10; STT (single-task training) group: sample size = 11.

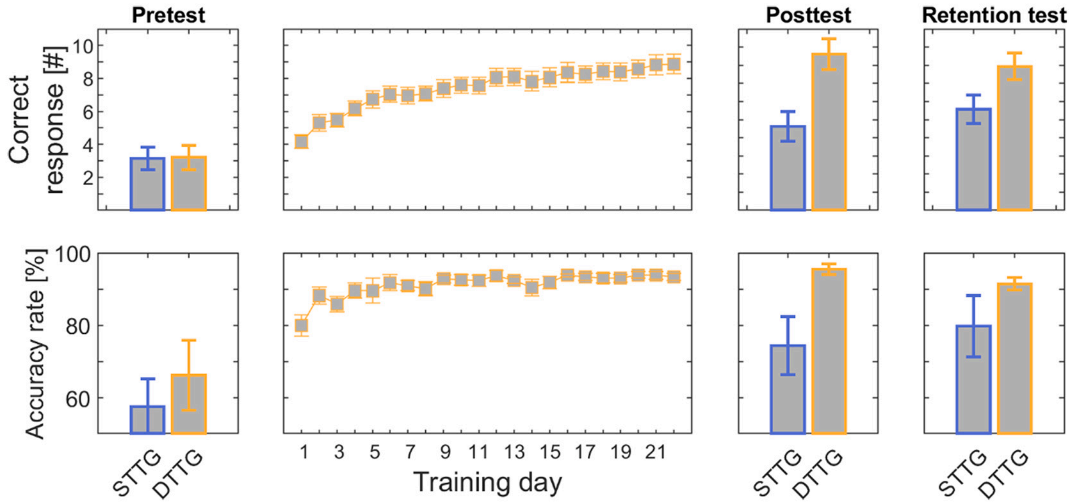

Fig. 6. Cognitive performances for each test session and training group, and training-related performances for dual-task training group. STTG = Single-task training group; DTTG = Dual-task training group. Mean ± SE.

3.4. Motor performance during training

Fig. 7 depicts the averaged values of all segments of RMSE ($\bar{x}$) values and of SIMI ($\bar{x}$) per training group and shows clearly that both training groups improved the motor-related parameters over training in general. Specifically, we were interested in differences between groups. The results from the two-factorial (Day: 1, …, 22; Segment: $PT_{repeated}$, PT_{random}) mixed (Group: STT, DTT) repeated measures ANOVA for the dependent variable RMSE show no clear main effect in the factor Day, $p = .067$, and no Segment main effect, $p = .610$. However, there is a Day × Segment × Group interaction in RMSE, $F(21, 399) = 1.678$, $p = .032$, $\eta_p^2 = 0.081$. For SIMI, we only found a Day × Group interaction, $F(21, 399) = 1.674$, $p = .032$, $\eta_p^2 = 0.081$. In both measures, group DTT started on a lower performance level. After about half of the training sessions, they reached a similar performance level as group STT. For RMSE, group STT showed implicit knowledge earlier, i.e., repeated segment was better performed compared to the random segment, than group DTT. Looking at both groups separately, we found a Segment main effect indicating implicit knowledge in the STT group, in RMSE, $F(1,10) = 6.334$, $p = .031$, $\eta_p^2 = 0.388$, and in SIMI, $F(1, 10) = 9.541$, $p = .011$, $\eta_p^2 = 0.488$. In Fig. 7, all Segment effects indicating implicit learning over the training period are depicted as relative Δ values for each training group and motor-related parameter, separately. The DTT group showed no Segment main effect. However, a Day × Segment interaction in RMSE, $F(21, 189) = 2.394$, $p = .001$, $\eta_p^2 = 0.210$, indicated better performance in the repeated segments halfway through the training sessions. In SIMI, there was a strong main effect of Segment, $F(1, 9) = 33.222$, $p < .001$, $\eta_p^2 = 0.787$, indicating a better performance in the repeated segment.

Overall, we found that both groups improved tracking performance from the beginning to the end of the training (see the panels for

Table 2
Averaged performance data with standard deviation within brackets per training group and task condition for the tracking segments at each test session. RMSE relies on the absolute distance of the force values, while SIMI quantifies time-locked coherence via correlation.

	RMSE [%]				SIMI			
	STT (n = 11)		DTT (n = 10)		STT (n = 11)		DTT (n = 10)	
	ST	DT	ST	DT	ST	DT	ST	DT
Pretest								
$PT_{repeated}$	20.9 (2.8)	23.6 (4.4)	21.8 (3.6)	24.2 (5.6)	0.55 (0.17)	0.50 (0.17)	0.51 (0.21)	0.50 (0.20)
PT_{random}	22.8 (3.4)	25.3 (4.4)	25.2 (7.1)	24.6 (4.0)	0.46 (0.18)	0.44 (0.19)	0.43 (0.21)	0.42 (0.21)
CT	21.7 (3.8)	25.3 (7.1)	22.2 (2.9)	24.8 (4.0)	0.53 (0.15)	0.42 (0.22)	0.56 (0.16)	0.48 (0.19)
Posttest								
$PT_{repeated}$	14.2 (3.0)	15.9 (2.5)	14.1 (1.5)	14.4 (2.2)	0.86 (0.01)	0.83 (0.04)	0.88 (0.04)	0.89 (0.03)
PT_{random}	15.1 (2.8)	16.6 (1.9)	15.2 (2.4)	15.1 (2.1)	0.82 (0.07)	0.79 (0.09)	0.83 (0.04)	0.83 (0.05)
CT	15.0 (3.8)	16.4 (2.8)	16.5 (2.4)	16.0 (1.8)	0.84 (0.06)	0.81 (0.05)	0.83 (0.07)	0.84 (0.05)
Retention								
$PT_{repeated}$	14.3 (2.6)	15.7 (3.0)	15.0 (1.8)	15.0 (2.1)	0.86 (0.05)	0.83 (0.06)	0.86 (0.04)	0.87 (0.04)
PT_{random}	15.0 (2.4)	16.5 (3.2)	15.9 (1.9)	15.8 (2.4)	0.81 (0.09)	0.79 (0.07)	0.80 (0.06)	0.83 (0.06)
CT	15.1 (3.7)	16.7 (3.7)	17.2 (2.5)	15.3 (1.7)	0.82 (0.08)	0.81 (0.08)	0.82 (0.05)	0.87 (0.05)

DT = dual-task condition; DTT = dual-task training group; ST = single-task condition; STT = single-task training group; CT = catch trials; PT_{random} = averaged random segments of the practice task; $PT_{repeated}$ = repeated segment of the practice task; RMSE = root-mean-squared error; SIMI = shortcut for similarity.

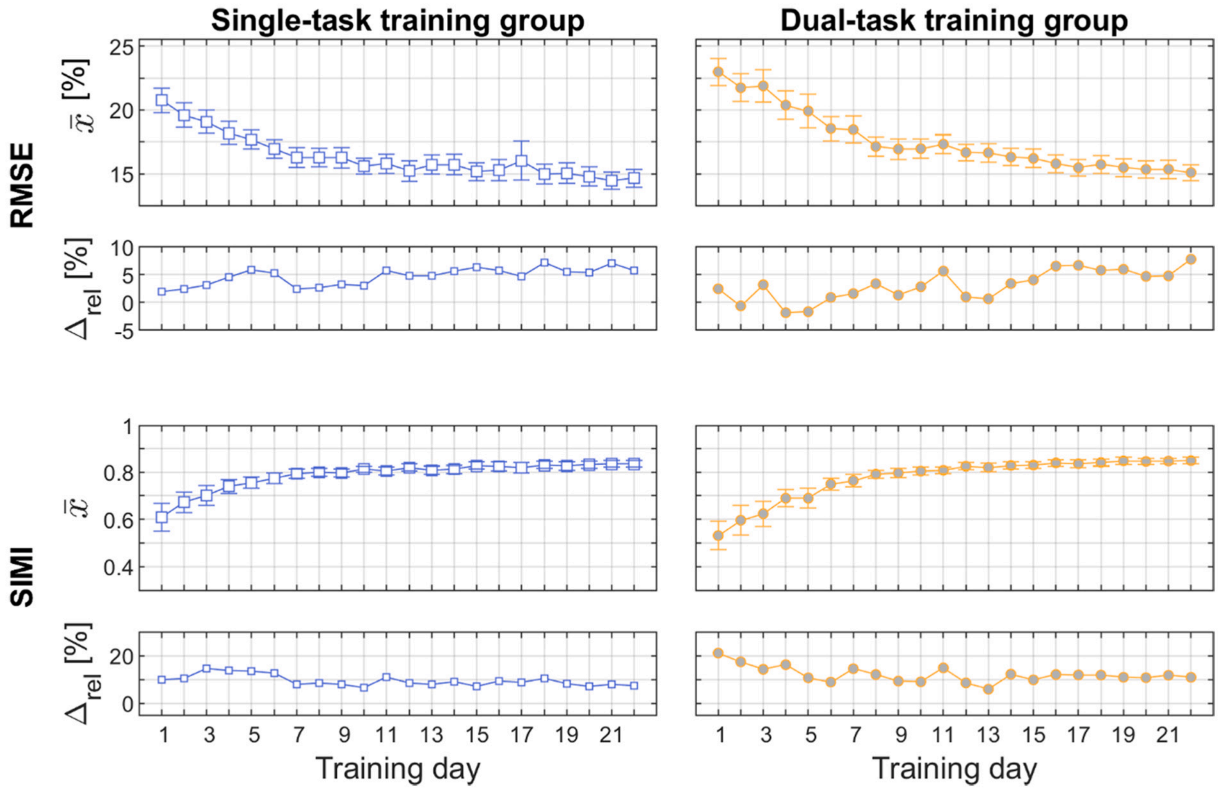

Fig. 7. Averaged motor performances over all segments ($\bar{x}$) and relative differences between $PT_{repeated}$ and PT_{random} segments (Δ_{rel}) for training days for the single-task training group (left column) and the dual-task training group (right column). Positive values for Δ in both parameters indicate better performed $PT_{repeated}$ segment compared with PT_{random} [RMSE Δ_{rel}: (PT_{random} − $PT_{repeated}$)/ PT_{random}•100, and SIMI Δ_{rel}: ($PT^2_{repeated}$ − PT_{random}^2)/ $PT^2_{repeated}$•100]. Error bars for $\bar{x}$ represent the standard error of the mean. Please note, RMSE basically relies on the absolute distance of the force values, while SIMI quantifies time-locked coherence via correlation.

the progress of the group averages $\bar{x}$ over time for RMSE and SIMI in Fig. 7). As hypothesized, the DTT group started from a lower performance level. However, unexpectedly, DTT group showed similar performance levels compared with the STT group at the end of training. Furthermore, the STT group showed similar implicit knowledge in RMSE and SIMI represented by the relative performance difference between repeated and random segments Δ_{rel}. As shown in Fig. 7, the relative difference in RMSE continuously increased with training from about 5% up to 10% almost linearly, whereas SIMI remained at a constant level of about 9.5 ± 2.4%. The DTT group showed such differences in RMSE later than the STT group. In contrast, Δ_{rel} demonstrated through SIMI started on a higher level of about 18% and decreased over time to an average value of about 12.0 ± 3.3% similar to the STT performance level.

3.5. Implicit learning and dual-task performance after terminating the training

In order to investigate the effects of the training condition on implicit knowledge and dual-task motor costs in RMSE and in SIMI, we conducted three-factorial (Test: posttest, retention test; Segment: $PT_{repeated}$, PT_{random}, CT; Load: single task, dual task) ANOVAs for each group, separatly, and with Group as a between-subjects factor.

3.5.1. Single-task training group

There was neither a Test main effect regarding posttest and retention test nor a Test-related interaction in RMSE and SIMI, all $ps \geq 0.178$. Given these results, indicating that posttest and retention tests show comparable effects, we pooled data across post- and retention test for display in Fig. 8 (see Table 2 for test-related single results). We did not find a significant Segment main effect in RMSE, $F(2,20) = 2.496$, $p = .108$, $\eta_p^2 = 0.200$. However, in SIMI, $F(2, 20) = 4.281$, $p = .028$, $\eta_p^2 = 0.300$, we found significantly better performance in $PT_{repeated}$ only compared with PT_{random}, $t(10) = 2.921$, $p = .025$, Cohen's $d = 0.881$. This pattern of results only partially confirms the observations from the training period. In SIMI, implicit knowledge was still found for the practiced task compared to the random segments.

In terms of motor dual-task costs, we observed strong Load main effects in both parameters. RMSE under dual-task conditions was larger than under single-task conditions, $F(1, 10) = 12.465$, $p = .005$, $\eta_p^2 = 0.555$, as was SIMI smaller, $F(1, 10) = 14.360$, $p = .004$, $\eta_p^2 = 0.589$.

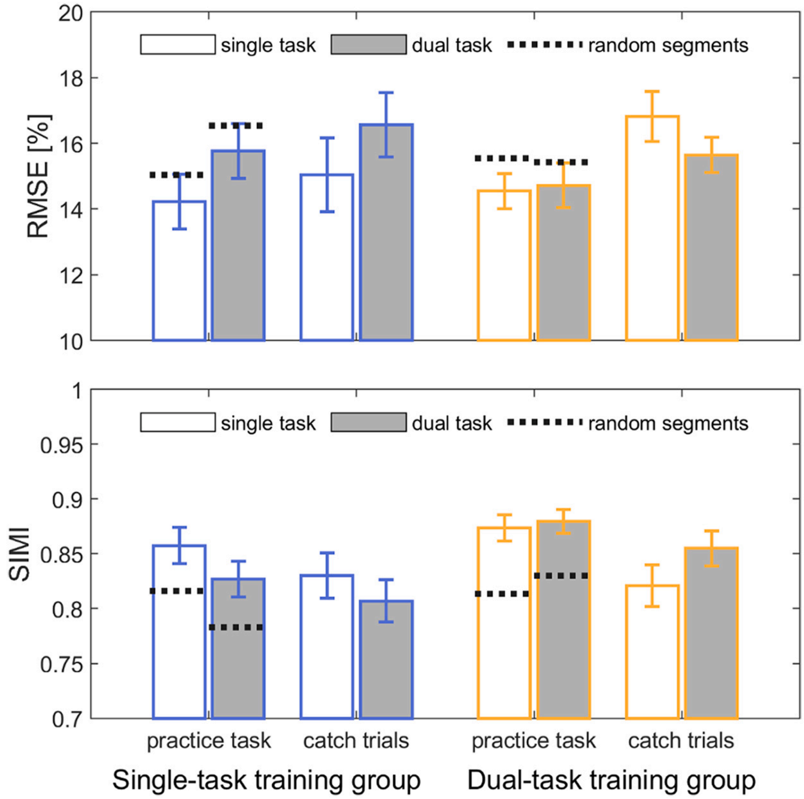

Fig. 8. Single-task and dual-task motor performances in the practice task (PT) and catch trials (CT) for pooled posttest and retention test. Bars show the performance of the repeated segment (mean ± SE). Dotted lines indicate the mean of random-segments performance for the respective practice-task conditions. Upper row depicts RMSE measure that relies on the absolute distance of the force values, where smaller values indicate higher accuracy in the tracking task. Lower row represents SIMI measure that quantifies time-locked coherence via correlation, where higher values indicate higher coherence between the force template and produced force.

3.5.2. Dual-task training group

Analogous to the STT group, we checked for performance differences at post- and retention test in the DTT group. With respect to the adjusted α-level, we found a Test × Load interaction in SIMI, $F(1, 9) = 1.770$, $p = .084$, $\eta_p^2 = 0.295$, where Test-related *post-hoc t*-tests revealed no significant effects, all $ps \geq 0.150$. Only at the retention test, single-task performance was worse than dual-task performance, $t(9) = -3.205$, $p = .030$. For RMSE, there was neither a Test main effect nor a Test-related interaction, all $ps \geq 0.172$. Hence, we depict the performances with pooled data including both posttest and retention test data in Fig. 8. Moreover, significant Segment main effects were found in RMSE, $F(2, 18) = 6.898$, $p = .006$, $\eta_p^2 = 0.434$, and SIMI, $F(2, 18) = 13.361$, $p < .001$, $\eta_p^2 = 0.598$ (see Table 2, and Fig. 8). Post hoc *t*–tests for RMSE revealed best performance in the $PT_{repeated}$ segment compared with CT. However, $PT_{repeated}$ and PT_{random} did not significantly differ from each other, i.e., implicit knowledge for RMSE is observed between the mid-segments of the practiced task and the catch trials, however, not between the segments within the practiced task. In contrast, the SIMI measure revealed the best performance for $PT_{repeated}$ compared with all other segment types, PT_{random}: $t(9) = 5.024$, $p < .001$, Cohen's $d = 1.589$; CT: $t(9) = 3.567$, $p = .007$, Cohen's $d = 1.128$. This indicated that the most robust implicit knowledge lies in temporal tracking characteristics. Finding this evidence for implicit knowledge, we expected that motor performance would not suffer under dual-task conditions. This indeed was the case, as no Load main effect for RMSE was found, $p = .332$. Surprisingly, in SIMI we found a Load main effect, $F(1, 9) = 6.799$, $p = .028$, $\eta_p^2 = 0.430$, and a Load × Segment interaction, $F(2, 18) = 3.616$, $p = .048$, $\eta_p^2 = 0.287$. This means that SIMI revealed a better coherence of 0.019 (SE: 0.007) under dual-task conditions than under single-task conditions. More specifically, differences between dual-task and single-task performances in the described direction became significant in CT, $t(9) = 3.611$, $p = .024$, whereas the practice-task segments did not show significant differences.

3.5.3. Performance differences between training groups

Further, we were interested in training type-related differences in implicit knowledge, i.e., interactions between Group and Segment and/or cognitive Load and/or Test session. We only found a significant Group × Load interaction, in both RMSE and SIMI; RMSE: $F(1, 19) = 11.044$, $p = .004$, $\eta_p^2 = 0.368$, and SIMI: $F(1,19) = 20.452$, $p < .001$, $\eta_p^2 = 0.518$. *Post-hoc* comparison of single-task and dual-task condition showed a larger Load effect for the STT group for RMSE: 1.5%, $t(10) = -3.868$, $p = .006$, and a dual-task decrement of about 0.029 (SE: 0.007) in SIMI, $t(10) = -3.982$, $p = .005$. In contrast, DTT group showed no more Load effect neither in the RMSE, $p = 1.0$, nor in the SIMI, $p = .120$.

3.6. Frequency analysis

Lastly, we were interested in the relative power in the specific frequency bands produced during training. The low frequencies (i.e., <1 Hz) are mainly associated with following the basic tracking curve, whereas frequencies between 1 and 2.5 Hz represent smaller corrective movements associated with closed-loop control. If group STT used a primarily closed-loop strategy, we would expect more power in higher frequency components during training compared to group DTT. In the latter group, we expected more use of open-loop control, as demonstrated by more power in low frequency components. Fig. 9 shows the relative power of both frequency bands for each group over training days. We compared the early training period (i.e., day 1 to 3) with the late training period (i.e., day 20 to 22) and observed an increment in relative closed-loop contribution for each segment during training, $F(3.281, 62.334) = 18.054$, $p < .001$, $\eta_p^2 = 0.487$. Predominantly higher frequencies were used by group STT, $F(1, 19) = 5.950$, $p = .025$, $\eta_p^2 = 0.238$. However, lower frequencies were used to an equal amount in the early and late training periods by both training groups, $F(1, 19) = 2.430$, $p = .136$, $\eta_p^2 = 0.113$. Surprisingly, there was a Segment main effect for the low frequency spectrum, $F(1.554, 29.522) = 17.668$, $p < .001$, $\eta_p^2 = 0.482$, showing smaller relative power in the first (a random) segment compared to the following (the repeated and the second random) segments, $p < .001$, Cohen's $d \leq -1.094$.

4. Discussion

Our study investigated implicit learning in a compensatory tracking task under single (STT) and dual-task training (DTT) conditions. Previous studies have shown that these training conditions differ in the degree to which attentional resources are available for tracking task control (Ewolds et al., 2017). We further assumed that to some extent closed-loop and open-loop control strategies require different contribution of attentional resources (Beilock et al., 2002; Kristeva-Feige et al., 2002; Wulf & Lewthwaite, 2016). Accordingly, we predicted that STT and DTT will facilitate different proportions of closed-loop (i.e., feedback based) and open-loop (i.e., feedforward based) contributions to motor learning. We used two different measures to quantify performance. One measure (RMSE) relies on differences between target force and actual force value, whereas the other (SIMI) uses correlations to quantify time-locked coherence between produced force and tracking template. We assumed these measures to be differentially sensitive to closed-loop and open-loop motor control. We also looked at power in different frequencies of force adjustments as an additional measure quantifying closed-loop control. Compared to other studies, we implemented an extended training period over several weeks. We monitored all performance measures across 22 out of 24 training sessions, a posttest, and a retention test.

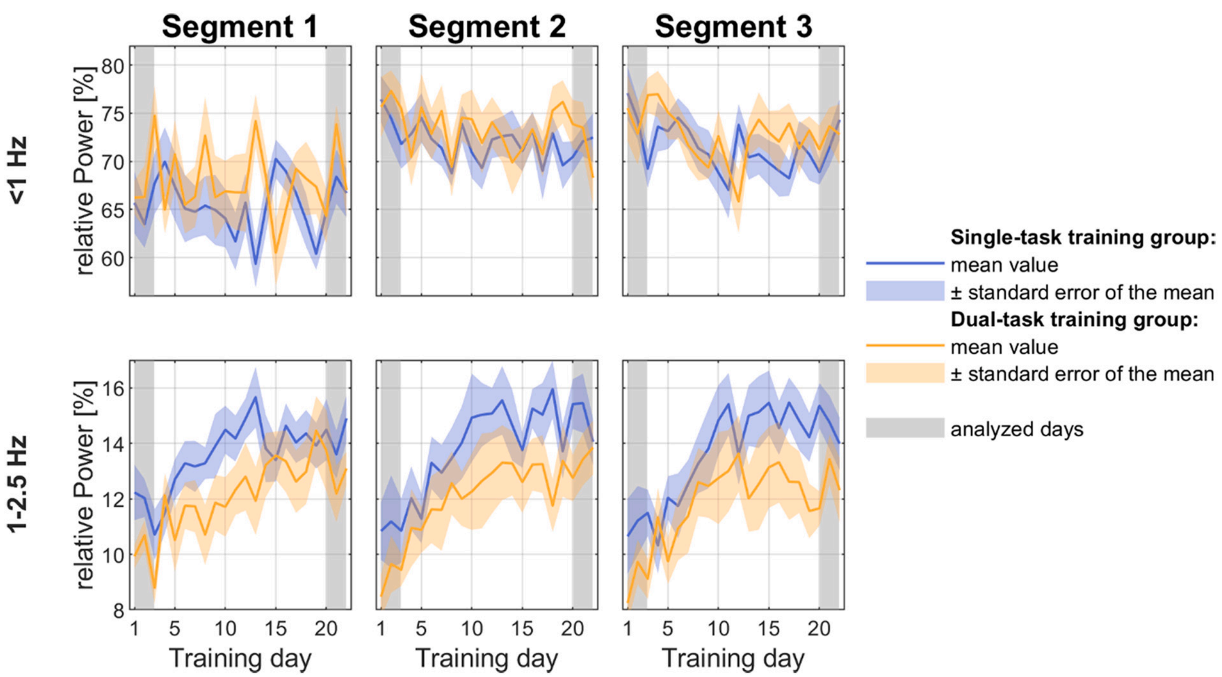

Fig. 9. Area plots of the relative power for two different frequency spectra for each training group. The upper row focuses on the development over practice of power in low frequencies, whereas the lower row shows the changes in the higher frequency band.

4.1. General changes in tracking performance

As desired in cross-sectional training studies, in pretest, average tracking performance was comparable between both training groups. Additionally, in pretest, the repeated and random segments were performed on a similar level confirming neither specific prior knowledge nor differences in the difficulty between the segment categories. After about six weeks of practice, tracking performance was clearly improved in both groups. These improvements persisted until the late retention test conducted after eight to 12 weeks without training. Furthermore, because most training studies suggest lower training improvements for DTT compared to STT (de Oliveira et al., 2017; Ewolds et al., 2017), we hypothesized that STT would outperform DTT in tracking performance after learning. However, surprisingly, this hypothesis must be rejected. The discrepancy of our results to previous observations can be explained by the extended training regime. We trained participants over at least 22 days, whereas in most of the implicit learning studies using the pursuit tracking paradigm pretest, training, posttest and retention test are all performed within at most three days (e.g., de Oliveira et al., 2017; Ewolds et al., 2017; Yang et al., 2017). This extended training thus ensured that both open-loop and closed-loop control mechanisms had sufficient time to develop. This was possible by taking advantage of not only the sheer number of training sessions, but also the amount of rest between trials and sessions, which have been shown to be crucial for optimal learning outcomes in many tasks (Nemeth and Janacsek, 2011; Walker, Brakefield, Morgan, Hobson, & Stickgold, 2002). This interpretation is also supported by the observation that DTT group started with smaller performance increases in the first training days, but then catching up, so that both groups reached a similar level at the end of training. Hence, we could demonstrate that while DTT might require more trials than STT to reach similar performance levels, the performance level set by STT is not out of reach for DTT protocols. Thus, looking at extended periods of training, as has been done in our study, is not a matter of implementing "more of the same" but rather a means to reveal new insights into motor learning, or in our particular case, implicit learning.

4.2. Evidence for implicit learning

While none of the groups could report knowledge about the task regularities, both groups showed implicit learning after training as indicated by a better performed repeated segment compared to random segments. Yet, there were differences between groups with respect to the robustness of this training effect against catch trials. In STT group, we saw indications of implicit learning only in the SIMI measure. In DTT group, evidence for implicit learning was also more pronounced in SIMI, but we additionally saw reduced RMSE values for the repeated segment compared to catch trials. The implicit knowledge in SIMI can be interpreted as performance benefits due to a learned inner template, reflecting the time course of the constant middle segment. To some extent, the findings are in line with Lang et al. (2011), who reported implicit learning in the SIMI measure for both STT and DTT regimes. However, as we could not test tracking performance with occluded feedback, we cannot infer, how the inner template of the repeated segment is used in the preplanning processes. Notably, in our study we found less robust implicit knowledge in the STT group. This suggests that, when closed-loop control is facilitated during training, implicit knowledge may be less stable against new learning experiences compared to when open-loop control is used more strongly, as seems to be the case in the DTT group. Interestingly, when the DTT participants were confronted with the new repeated segment in the catch trials, both performance measures suffered most under single-task condition, i.e., when closed-loop control is facilitated.

4.3. Effects of an added cognitive task on tracking performance

Besides tracking improvements, participants in DTT also enhanced their cognitive performance by not only tripling the number of calculations but also by increasing accuracy. This cannot be explained by the simple test repetition effect we observed in the STT group. The clear learning effect shows that DTT participants complied with the instructions and really invested at least some of their cognitive resources into the cognitive task. Furthermore, in the STT group, tracking performance always dropped when concurrently performing the tracking and the cognitive task in the test sessions. Thus, some of the cognitive processes required for the calculation task interfered with processes involved in tracking control. This is different for DTT group, where tracking performance stayed unaffected by additional cognitive requirements of the calculation task. We even see a tendency for an inverse effect. In catch trials, where we replaced the constant middle segment by an unknown trajectory, temporal coherence (SIMI) is better under dual-task compared to single-task test conditions. The prediction that predominant use of attentional resources by closed-loop tracking control would result in a performance drop when adding the secondary cognitive task was confirmed by the STT group. The observed motor costs are in line with resource theories of central processing and the underlying limitation of central processing resources (Kahneman, 1973). Processing two or more tasks concurrently should interfere when the tasks compete for the same processing resource, showing up as a performance decrement (i.e., motor costs here) under dual-task condition compared to single-task condition (Wickens, 2021). In this study, however, the DTT group resolved the motor costs in the practiced task. We suggest that this was possible through greater use of open-loop control while dual-tasking. Open-loop control is arguable more automatic and less dependent on attentional resources. Therefore, more central processing resources were available for secondary task processing.

So far, we have based our interpretations only on observations in the posttests. Before issuing further theories, it would be helpful to have a closer look at the training progress. This does not only regard performances as indicated by RMSE and SIMI, but also differences in power across different frequency components of tracking behavior.

4.4. Changes in contribution of control processes during training

Despite the fact that both groups reached similar performance levels in the tracking task at the end of the training period, there are clear differences in the profile of interference with the cognitive task. We hypothesize that these differences can be explained assuming that different practice conditions induce different proportions of open-loop and closed-loop motor control components in tracking control. We saw that both training groups showed a somewhat inverted profile, in how the performance benefits of the repeated segment over the random segments showed up in our performance measures. From the very beginning of practice, STT group continuously gained performance benefits reflected in RMSE, while SIMI improvements were visible only to a lesser degree. Contrastingly, DTT group showed early benefits almost exclusively in SIMI, while improvements in RMSE were mostly seen later in practice. In addition, both groups continuously increased the amount of corrective force adjustments, which is expressed in an increasing power in the frequency band that reflects such feedback controlled corrections. Yet, these increases were far more pronounced in STT compared to DTT group. Because this effect is not limited to the repeated segment, we interpret this gain in closed-loop control as a general training effect, which is not based on exploiting the specific regularities of the middle segment. Nevertheless, as expected for the STT group, the availability of attentional resources evoked a better closed-loop control shown by a primary performance benefit in RMSE, which is corroborated by higher power contributions in the upper frequency band. Additionally, we hypothesized that temporal coherence (SIMI) simply increases with reduced spatial deviation (RMSE) (see Fig. 1 C and D) expecting no important SIMI effect in the STT group for the posttests after a stronger closed-loop controlled training. However, we found that there was processing even of the temporal task regularities in the compensatory tracking. Although, we cannot specify where and when implicit knowledge represented by the SIMI measure developed in the STT group and how the DTT group precisely scheduled the processing of all task demands, both groups seemed to follow motor control strategies, which were influenced by the respective amount of available attentional resources during training.

4.5. Evaluation of the power of the study, the motor outcome measures, and the motor task

Suboptimal power due to dropout of participants who did not comply with instructions may have played a role in our study. Non-compliance entailed, for instance, participants in the DTT group who stated to prioritize the motor task or the cognitive task, whereas the participant in the STT group felt bored by just performing the motor task and started actively learning for their upcoming exams in parallel. These observations point to individual differences in dual-tasking, which seem to be hard to overcome for some people. Some other participants did not apply force adjustments as instructed but rather pressed against the force plate constantly, indicating possible motivational deficits. For the current findings, smaller power is a limitation even if the training groups are almost of similar sample size. However, given that we used rather conservative parameters for calculating the sample size, we argue that the strong correlations between the test sessions would reduce the lack in the *post-hoc* power estimation. Thus, the smaller sample should still represent valid characteristics in implicit learning for each motor parameter and each group.

In line with Yang et al. (2017), we hypothesized and found SIMI to be more sensitive to implicit learning effects than RMSE. There are several reasons why RMSEs might not reflect implicit learning of wave forms in the same way as SIMI. The first is that SIMI, which corresponds to the wave specific information, captures amplitude changes in movement better than RMSE. Another reason is that RMSE is more sensitive to errors and outliers, whereas SIMI, as a parameter based on correlations, partially masks this by focusing more on the correct global reproduction of the wave form. While SIMI detected learning early on, particularly for DTT group, RMSE seemed to become more important to indicate practice-related benefits later on. This can be explained by the fact that open-loop control based on implicit knowledge is less susceptible to time delays than closed-loop control, because the knowledge can lead to anticipation of the position of the target. Therefore, later in practice, when implicit knowledge has increased or the application of implicit knowledge has been optimized, the occurrence of time-lags due to closed-loop control should become less common and RMSE becomes a more sensitive measure. Then, the RMSE parameter can be used to target the effects of higher order control on peripheral movement execution without losing information regarding lower-order motor control resources. However, RMSE and SIMI do not only allow the explanation of implicit learning by certain motor control mechanisms, but may also provide specific practical support to learners. In detail, for the purpose of enhancing compliance and to keep the power in such elaborate studies, the feedback on motor performance could be modified in accordance to the current results. In our study, feedback was provided only by the linearized RMSE. However, assuming that SIMI is more important in the beginning of implicit learning in compensatory tracking, feedback on this particular performance measure may be more helpful in early learning and perhaps also in compliance.

Furthermore, analyzing power in different frequency bands of force alterations seems a promising method to disentangle closed-loop and open-loop control, although there were some surprising findings as well. We only found different power contributions between the first segment and the following segments in the slow frequency band, but not between the random segments and the repeated segments in general. In addition, the inter-individual variability in the use of higher frequencies is large, which is in accordance with observations by Miall (1996), however, complicates the categorization. Therefore, individually calibrated frequency analyses and incorporation of time-lags might improve this method and should be the goal of future studies.

Finally, yet, it remains unclear whether the findings on implicit learning and dual-task processing of our tracking task is valid for other tasks, as the motor task in the current study was rather easy, because there was only one dimension for motor coordination (Wulf & Shea, 2002). Nevertheless, we would like to highlight the novelty of using a force-tracking apparatus compared to other devices. The benefit is that in isometric force tracking, the measured force is a direct output of the control system. This is different for measures relying on kinematic measures like the position of an object or body part. Measured positions reflect control output only indirectly, since applied forces first need to overcome inertia of the moved object and body parts. Thus, object position can always only be seen as a smoothed and delayed correlate of force control. Using a joystick or a computer mouse reduces movement extent and the masses that need to be moved. Yet, our isometric task alleviates these limitations even further, despite involving large muscle groups. This allows for more fine-grained analyses of time-related control activities, in our case, enabling the disentanglement of closed-loop and open-loop contributions.

5. Conclusion

Investigating isometric force adaptation and implicit learning in a compensatory tracking task allowed us to draw conclusions about the motor control strategy (i.e., open-loop or closed-loop control) used in implicit motor learning under single task and under dual-task conditions. We can demonstrate that after a sufficient amount of training, single motor-task training elicits more closed-loop control, while dual-task training promotes more open-loop control. This increased reliance on open-loop control could explain more robust implicit learning effects and larger reductions of motor costs after dual-task training.

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CRediT authorship contribution statement

Christine Langhanns: Conceptualization, Methodology, Software, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration, Investigation. **Harald Ewolds:** Writing – review & editing. **Stefan Künzell:** Conceptualization, Methodology, Writing – review & editing, Funding acquisition. **Hermann Müller:** Conceptualization, Methodology, Resources, Supervision, Writing – review & editing, Funding acquisition.

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