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ABSTRACT

In this experiment, we compared changes in visuomotor performance and motor control after a single session of differential learning (DL) and contextual interference (CI) in a reaching task to mimic goalkeeping. Subjects ($n_{DL} = n_{CI} = 16$) stood in front of a wall with six LED-light targets that flashed on in a random order and subjects had to move their hand in front of it as fast as possible in order to extinguish the target. After the pre-test subjects followed a DL or CI training session, followed immediately by a post-test, followed by one hour of rest and a retention test. Performance and motor control were measured respectively by visuomotor response time (VMRT) and an Index of Motor Abundance (IMA; reflecting the strength of movement synergies) calculated with Uncontrolled Manifold analysis. A mixed-effects Bayesian ANOVA model was used to evaluate differences in changes in both parameters between both training groups. Averaged over the six targets, the decrease in VMRT was stronger for DL than CI at the post-test (interference effect) but not at retention. The IMA was on average increased at post- and retention test in both groups, indicating stronger synergies between the degrees-of-freedom. While the ANOVA for IMA was not conclusive, the changes were likely not different between both learning methods. Thus, while an interference effect was found for CI but not DL in terms of performance on the task, no such effect was observed on the behavioral level in terms of the strength of movement synergies.

Keywords: Differential Learning, Contextual Interference, Visuomotor Response Time, Uncontrolled Manifold, Bayesian statistics, Statistical Parametric Mapping

INTRODUCTION

Improving visuomotor response time (VMRT) is important for various performance-related tasks in sports contexts like goalkeeping. Making correct split-second decisions on where the target will be and initiating a proper motor response can make an important difference between winning or losing a game. Several motor learning paradigms exist that can guide training practices for improving VMRT.

Differential Learning (DL) is a motor learning model grafted on the importance of movement variability and is rooted in dynamical systems theory of human movement (Schöllhorn, 1999, 2000). By introducing variability during practice –by performing different movement variants, changing the constraints of the task, etc.– DL aims to let subjects explore their individual-specific and time-dependent motor landscapes in order to let them find optimal solutions to a given movement task (Schöllhorn et al., 2010). By practicing a particular VMRT task using several variations, DL may help a subject to find, implicitly, a specific motion pattern (preparation/readiness pose, movement initiation, relative velocity of joints of the upper limb, ...) suited to his/her constraints. DL has demonstrated positive performance effects in several experiments on relatively isolated motor tasks where subjects may prepare and initiate the movement themselves, e.g. soccer kicks (Schöllhorn et al., 2006), shot putting (Beckmann et al., 2006), handball throwing (Wagner & Müller, 2008) and volleyball service (Reynoso et al. 2013), but not yet in tasks whith dynamic contexts and involving cognitive-motor coupling like reacting to a stimulus and then initiating a fast motor response as in goalkeeping.

Compared to Contextual Interference (CI), another motor learning model based on movement variability (Magill & Hall, 1990; Brady, 2004, 2008), DL is different in several aspects (Hossner et al., 2016a, 201b, Schöllhorn, 2016), most notably in the absence/reduction of the diminished short-term acquisition rate (interference effect). By practicing a number of (related) movements simultaneously, CI may result in enhanced learning rates on retention tests but generally causes diminished improvements on acquisition tests. Holmberg (2009) advocated the use of CI for training agility, of which VMRT is an important aspect. Higher CI under random practice leads on average to stronger interference effects compared to low CI with blocked practice (Brady, 2004). Schöllhorn (2009) discussed a unified model of motor learning methods that can be arranged along a continuum of increased practice variability. While DL presents clearly greater amounts of variability than the highest levels of CI, DL experiments do not show interference effects (Schöllhorn, 2016). While several experiments have compared DL to classical paradigms as repetitive practice and methodological series of exercises (Serrien et al., 2018), only one study compared learning rates between DL and CI. Beckmann et al. (2010) compared CI with three different implementations of DL to improve the accuracy of field hockey push and flick shots at goal. They found quite heterogeneous results for both movements, with none of the training methods being consistently better on post-test, transfer-test and retention tests, and no clear interference effects in CI. Hockey push- and flick motions are quite complex however, including many biomechanical degrees-of-freedom, where interference phenomena are generally lower (Brady, 2008). In this study, we will use a standing perception-action reaching task to mimic goalkeeping. This is still a multidimensional movement, but may be constrained to a standardized task to contain fewer relevant degrees-of-freedom so that we may compare motor learning interference in DL and CI directly.

Short-term DL based on a single training session has been successful in terms of performance in one previous study on postural control (James, 2014). Other studies found short-term effects of DL and CI, and differences therein, at the level of electroencephalopgraphy activity (Henz & Schöllhorn, 2016; Henz et al., 2018). With the present study, we aim to contribute further to the understanding of how DL and CI differ at the behavioural level. While the rationale for DL comes from intrinsic movement variability on multiple time scales (Schöllhorn et al., 2009, Schöllhorn et al., 2010), hitherto no study has examined the effects on this intrinsic variability. In this study, we will therefore include motion capture during the task and use Uncontrolled Manifold (UCM) analysis (Scholz & Schöner, 1999) to study potential changes in the structure of movement variability. Because DL focuses not on how exactly a movement is performed, but rather on finding individual optimal solutions, UCM is particularly suited for this analysis as it can be done at the individual level and can take all relevant degrees-of-freedom into account simultaneously.

Summarizing, in this study we will use a goalkeeping mimicking task before and after a single session of DL or CI to examine if there are differences in the rate of changes in performance and motor control. In line with the different predictions of interference effects by DL and CI, we hypothesize to see stronger improvements in VMRT at the post-test for DL, but smaller differences at the retention test. For the motor control outcomes of UCM analysis, no specific hypothesis is set forward as this is the first study examining this in DL. The aim of the UCM outcome is to help elucidate how DL and CI may lead to different outcomes in VMRT of the reaching task.

MATERIALS and METHODS

Design. Randomized two-group pre-post-retention test design. Blinding of subjects and researchers was not possible, but subjects were not made aware of the study goal and its hypotheses. When participants had completed the study, we informed them about the goal and its hypotheses. Data registration for the performance and behavioral variables was computer-controlled. This study was approved by the Medical Ethics Committee of Vrije Universiteit Brussel/University Hospital Brussels (B.U.N. 143201837255).

Subjects. Subjects had to visit the lab once (± 2.5 h per subject) and were recruited at the faculty of Physical Education and Physiotherapy of the Vrije Universiteit Brussel. All subjects were students or teaching/research assistants in physical education, movement science, physiotherapy or manual therapy. All subjects were free of injury at the time of the study and signed informed consent forms. At enrolment, subjects were randomly allocated to one of two training sessions (DL or CI) by a random selection of a 0/1 from a balanced list (LibreOfficeCalc).

Task and performance measure. The task took place in a semi-darkened room. The task was conceived as a complex response time paradigm, mimicking a goal-keeper in team-handball or indoor soccer. The subject had to stand in front of a wall, at a comfortable distance (typically 40-50 cm), to which two columns of three LED-lights (Fitlight Trainer^{TM}, FITLIGHT Sports Corp., Aurora, Ontario, Canada) were attached (see Figure 1). The subject stood in the middle of the two columns. They received the instruction to take a goal-keeper-like position in order to be able to reach to the lights as fast as possible. The LED-light targets were programmed to flash on (red light) in a pseudo-random order upon which the subject had to move his/her hand in front of the LED-light target as fast as possible to turn off the light. There was no need to touch the LED-light target, the sensors sensed the presence of the hand from 10 cm distance (diminished light entry). The LED-lights were programmed so that when the subjects turned off a LED-light target, there was a 2.5 s refraction period before the next target flashed on so that subjects had enough time to return to their preferred start position but not so much as to relax between two trials.

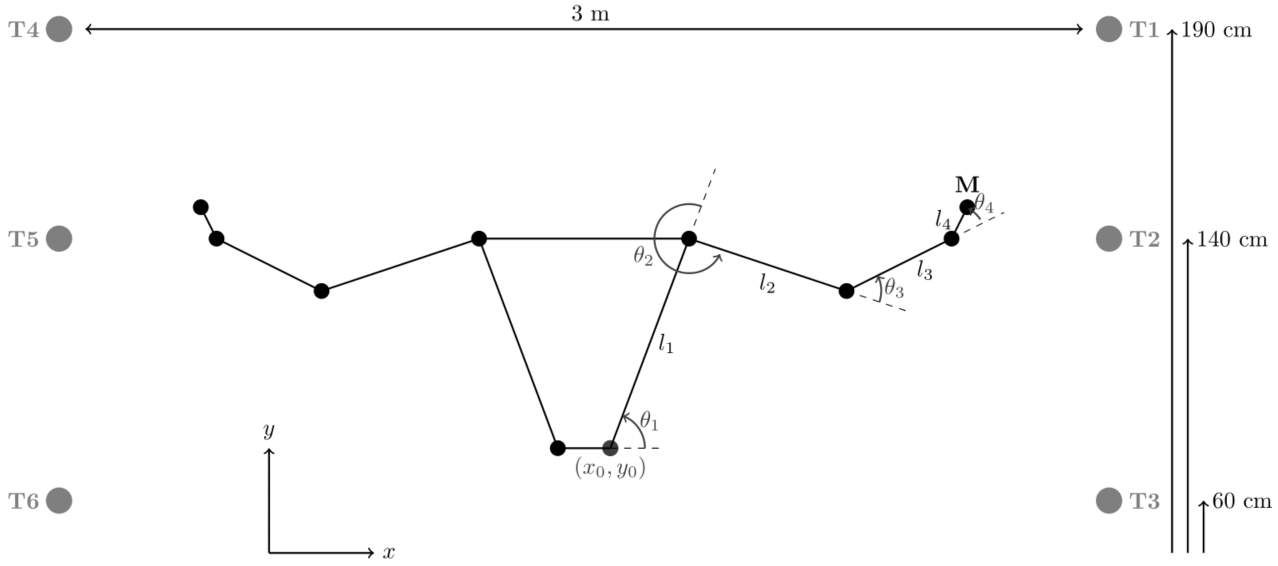


Figure 1: Task setup and definition of joint angles for the UCM (not to scale). T1 – T6 are the Fitlight targets. Black circles represent the retroreflective markers. Segment lengths are indicated by l_i, these were entered as constants in the UCM and were measured when the subject stood in a T-pose during a static calibration trial. Gray points and arrows represent the six degrees of freedom (elemental variables) of the model. The degrees of freedom of the lower limb joints were not included separately, but their composite action is included through the location of the pelvis markers (x_0, y_0). The location of the metacarpal marker (M) relative to the flashing target was used as performance variable.

VMRT was saved automatically on a tablet. The LED-light targets were programmed so that when the subject had a response time of 1000 ms or more, the target was coded as a miss. Before the pre-test, subjects received a warm-up session of two series of thirty lights in order to acquaint themselves with the set-up and the sensitivity of the targets. After these two warm-up series, subjects received feedback on their mean response time and the number of targets that they missed, no feedback was given on their movement pattern or starting position. The pre- post- and retention test consisted of sixty targets in total (10 trials per target) divided over four series of fifteen targets in a row (30 s rest between series). During the tests, no feedback was given about VMRT, number of missed targets or movement pattern in line with previous studies on DL (Schöllhorn, 2016). The median VMRT over 10 repetitions per target was taken as performance measure.

DL and CI training session. The DL and CI training sessions consisted of 180 targets in total (duration ± 30 min), directly followed by the post-test. After the post-test, subjects had to rest for 1 h, followed by a warm-up (2×30 targets) and the retention test. The DL session was organized in 30×6 targets. In each series of 6 targets (random selection, targets could occur twice), subjects received a different instruction (and demonstration if necessary) from the researcher as to how they should move or what starting position they should take (see Appendix A1 for a list of all exercises). The CI session was organized in 2×3×30 targets (two times three exercises with each thirty repetitions; serial-blocked practice, see Appendix A1 for the exercises). After the training and before the post-test, subjects were asked to answer the following question (yes/no): "*Do you feel, subjectively, that one of the exercises, has learnt you something that might improve your performance on the task?*"

Motion capturing. During all three test occasions, subjects' movement patterns of trunk and upper limbs were recorded with six VICON MX F-20 cameras at 250 Hz sampling frequency. Retroreflective markers (14 mm) were attached to the skin with double-sided tape at (bilateral) spina iliaca posterior superior, acromion, epicondylus lateralis humeri, processus styloideud ulnae, caput metacarpalis III and middle phalanx of the middle finger. Because the experiment used only a single session, no offsets due to different camera calibrations and marker placements affected the analysis. Labelling, gap filling and filtering of marker trajectories (4th order zero-lag low-pass Butterworth filter, cutoff frequency 6 Hz) were done in VICON Nexus 1.8.2. When the Fitlights turned on and off, the cameras registered this as 'ghost markers' appearing and disappearing, which were used as time stamps in the analysis for defining the start and end of the reaching movement. The filtered marker coordinates were further analyzed in Python (Spyder IDE, Anaconda 2019) using Uncontrolled Manifold Analysis.

Uncontrolled Manifold Analysis. Analysis of the variability in coordination patterns was done with Uncontrolled Manifold (UCM) analysis (Scholz & Schöner, 1999). UCM decomposes total trial-to-trial variability (V_{TOT}) in the movement pattern into goal-equivalent variability ("good" variability, V_{UCM}) and non-goal equivalent variability orthogonal to the

UCM ("bad" variability, V_{ORT}) based on a linearization of the relationship between the elemental variables (degrees-of-freedom) and a hypothesized performance variable. The hypothesized performance variable in this study (***P***, dimension $n = 2$) was the relative position of the metacarpal marker (***M***) and the target location ($\boldsymbol{T_k}$, $k = 1, \ldots, 6$, calculated per target): $\boldsymbol{P} = \boldsymbol{M} - \boldsymbol{T}$ and was expressed in terms of the vector of elemental variables $\boldsymbol{E} = (x_0\ y_0\ \theta_1\ \theta_2\ \theta_3\ \theta_4)^{\mathrm{T}}$ (of dimension $m = 6$) as follows (see Figure 1):

$$\begin{bmatrix} P_x \\ P_y \end{bmatrix} = \begin{bmatrix} x_0 + \sum_{i=1}^{m} l_i \cos\left(\sum_{j=1}^{i} \theta_j\right) - T_x \\ y_0 + \sum_{i=1}^{m} l_i \sin\left(\sum_{j=1}^{i} \theta_j\right) - T_y \end{bmatrix}$$

Joint angles (θ_i) and position of the pelvis ($x_0\ y_0$) were computed per trial from the first point where the ghost markers appeared in the data file until the point where the last disappeared (i.e. full coverage of the light by the hand) and they were subsequently time-normalized to 101 datapoints (0-100% of the reaching movement). Because the joint angles of the left arm correspond to the null space of the task when a target on the right is activated, separate models were constructed for both arms as this simplified computation. The null space of the Jacobian matrix ***J***, $J_{ij} = \partial P_i / \partial E_j$ ($i = 1, 2$; $j = 1, \ldots, m$), was obtained using Singular Value Decomposition. The linearization of the Jacobian was done around the time-dependent mean value of the elemental variables: $\boldsymbol{J} \cdot \bar{\boldsymbol{E}} \cdot null(\boldsymbol{J}) = \boldsymbol{0}$, separate per target and per measurement session (pre-post-retention). Also the (co-)variance matrix **C** among the elemental variables, was estimated per target and measurement session. From the UCM analysis, the Index of Motor Abundance (IMA, a measure of the strength of the synergy between the elemental variables) was constructed at each percentage of the movement trajectory as follows (Tseng & Scholz, 2005):

$$V_{UCM} = \frac{trace(null(\boldsymbol{J})^t \cdot \boldsymbol{C} \cdot null(\boldsymbol{J}))}{(m-n) \cdot N_{trials}}$$

$$V_{ORT} = \frac{trace((\boldsymbol{J}\cdot\boldsymbol{J}^t)^{-1}\cdot\boldsymbol{J}\cdot\boldsymbol{C}\cdot\boldsymbol{J}^t)}{m\, N_{trials}}$$

$$IMA = \frac{V_{UCM} - V_{ORT}}{V_{UCM} + V_{ORT}}.$$

The UCM analysis was done at the individual level. The resulting IMA was selected as the primary outcome measure reflecting the motor control strategy. Positive IMA ($V_{UCM} > V_{ORT}$) reflects a motor control strategy where trial-to-trial variability in the patterns of the elemental variables is constrained in such a manner as to maintain stability of the performance variable; in the present context meaning that the position of the pelvis (representing lower limb actions) and joint angles of trunk and upper limb co-vary between trials as to maintain a consistent trajectory of the hand during reaching. At the post-test, the markers of four subjects fell off due to sweating which resulted in missing IMA data for them. Trials for targets T3 and T6 were excluded for all subjects because movement onset timing could not always be accurately determined from the Fitlight flashes in the VICON recordings.

Statistical analysis. Statistical analyses were performed in R (R Core Team, 2019) using the BayesFactor (Morey & Rouder, 2018) and HDInterval (Meredith & Kruschke, 2018) packages. Data and code are available at: https://osf.io/pf6xj/. Data for left-handed subjects were relabelled so that targets T1-T3 correspond to the dominant side and T4-T6 to the non-dominant side for all subjects. The change in median VMRT ($\Delta VMRT_{post} = VMRT_{post} - VMRT_{pre}$; $\Delta VMRT_{retention} = VMRT_{retention} - VMRT_{pre}$) was analyzed with a default Bayesian ANOVA model (Rouder et al., 2012) with group (DL vs CI) as a fixed factor. Target was included as a random factor as the locations can be seen as random points in a goal-keeping task. Subject ID was also included as a random factor to account for repeated measurements over targets. The default non-informative priors were chosen as no previous comparable study conveys substantive information on the expected effects. For the fixed and random factors, prior scales of $r = ½$ and $r = 1$ were used respectively. Sensitivity analyses were performed to assess robustness against specifications of the prior scales. The Bayes Factor (BF_{10}) compares the model including group (H_1) to the model with random effects only (H_0), i.e. testing whether subjects in DL had different learning rates than CI subjects. The *BF* quantifies the marginal likelihood ratio of the data under both competing hypotheses and does not suffer from some of the issues associated with *p*-values from NHST (Rouder et al., 2012). A heuristic classification of evidence levels indicates weak evidence for H_1 for a BF_{10} between 1 and 3, moderate 3-10 and strong > 10 (vice versa for $BF_{01} = 1/BF_{10}$ as evidence for H_0). Additional to the *BF*, posterior medians and 95% highest density intervals (HDI) were obtained for the difference between DL and CI as measures of effect size.

For the analysis of IMA time series, the same statistical model was fit for ΔIMA at each percentage of the movement pattern using a Bayesian analogue to one-dimensional Statistical Parametric Mapping (SPM; Pataky, 2012, Serrien et al., 2019). To deal with the multiple testing problem (101 time points), *BF*s were transformed to posterior probabilities (assuming a prior odds of 1 between H_0 and H_1) and either hypothesis was only accepted if a cluster had a posterior probability > 0.95 (keeping the false discovery rate below 0.05, Serrien et al., 2019).

The analysis of the response to the yes/no question about their subjective feeling of the effectiveness of the exercises was analyzed with a Bayesian contingency table with independent multinomial sampling.

RESULTS

Thirty-two subjects completed this study. Table 1 presents their characteristics and performance per LED-light target at the pre-test. Both groups are approximately comparable at baseline.

Table 1: Baseline characteristics of subjects per group (cells are mean ± SD [min - max]).

		DL	CI
N (male/female)		16 (13/3)	16 (12/4)
Age (yrs)		24 ± 2 [20 – 34]	23 ± 2 [19 – 35]
Height (cm)		176 ± 10 [157 – 190]	176 ± 12 [159 – 189]
Weight (kg)		74 ± 8 [56 – 91]	72 ± 7 [59 – 89]
Sport/exercise per week (hrs)		4 ± 1 [1 – 7]	4 ± 2 [1 – 10]
	T1	829 ± 99 [653 – 993]	832 ± 64 [732 – 986]
	T2	686 ± 50 [624 – 781]	676 ± 55 [590 – 802]
VMRT at pre-test (ms)	T3	861 ± 57 [779 – 955]	843 ± 62 [752 – 980]
	T4	854 ± 74 [748 – 998]	892 ± 70 [791 – 995]
	T5	664 ± 57 [558 – 773]	664 ± 84 [473 – 774]
	T6	871 ± 66 [749 – 974]	858 ± 64 [755 – 991]

VMRT. Table 2 presents ΔVMRT per target. The analysis of the short-term acquisition effect indicated very strong evidence for a difference in $\Delta VMRT_{post}$ between DL and CI ($BF_{10} \approx 8688.1 \pm 0.7\%$). Averaged over the six targets, subjects that received DL exercises showed stronger reductions in median VMRT than subjects in CI (posterior median and 95% HDI = -30 ms [-43; -19]). The difference in $\Delta VMRT_{retention}$ was also in favor of DL (85% of the posterior of the difference was negative), but the effect was small (median = -7 ms) and the 95% HDI covered zero ([-21; 6]). The hypothesis test even indicated weak evidence in favor of H_0 ($BF_{01} \approx 2.8 \pm 0.9\%$). Appendix A2 shows that these findings are robust over a range of the prior scale factor *r*.

IMA. The IMA trajectories were consistent over the four analyzed targets (T1, T2, T4, T5; see top panels of Figure 2 for descriptives of T1). The mean of ΔIMA is positive throughout nearly the entire movement, indicating that subjects have learned to increase the synergy strength between the elemental degrees-of-freedom. However, this increased synergy index was not found to be different between both learning methods. The bottom panels in Figure 2 show that H_0 was the more likely hypothesis during the entire movement for both post- and retention-test. Although, the criterion of 95% posterior probability was never attained (and H_0 could thus not be accepted), it remained relatively stable around 80% and never dropped below 50%. Sensitivity analyses on the prior scale factor show robustness of these findings (Appendix A2).

Subjective feeling of the learning experience. In the DL group, 13/16 subjects answered 'yes' to the question whether they felt they learned something that might improve their performance. In the CI group, only 7/16 responded positive. The test indicated moderate evidence in favor of the alternative hypothesis of a different response rate between DL and CI (BF_{10} = 4.025; posterior median and 95% HDI of the log odds-ratio: 1.56 [0.12 – 3.14]).

Table 2: Change scores in median response time (ms). Data are mean ± SD [min; max]. Negative values indicate faster performance on post/retention tests. See supplementary file S1 at https://osf.io/pf6xj/ for boxplots of the original data values per target and Bayesian posterior distributions of the marginal effects (averaged over targets).

	$\Delta VMRT_{post}$		$\Delta VMRT_{retention}$	
	DL	CI	DL	CI
Target T1	-56 ± 32 [-123; -18]	-6 ± 24 [-55; 49]	-77 ± 30 [-132; -40]	-55 ± 51 [-121; 17]
Target T2	-46 ± 30 [-109; -8]	-5 ± 27 [-62; 39]	-64 ± 37 [-138; -7]	-63 ± 22 [-105; -19]
Target T3	-40 ± 34 [-76; 36]	-6 ± 23 [-30; 44]	-57 ± 31 [-108; -1]	-70 ± 25 [-116; -11]
Target T4	-50 ± 58 [-174; 50]	-8 ± 23 [-50; 29]	-70 ± 58 [-192; 22]	-36 ± 44 [-103; 56]
Target T5	-27 ± 23 [-63; 11]	-22 ± 28 [-81; 38]	-56 ± 31 [-100; 18]	-54 ± 32 [-157; -18]
Target T6	-27 ± 13 [-53; -11]	-4 ± 44 [-114; 44]	-58 ± 29 [-104; -8]	-58 ± 37 [-129; 30]
Average	-40 ± 8	-9 ± 8	-63 ± 9	-56 ± 9

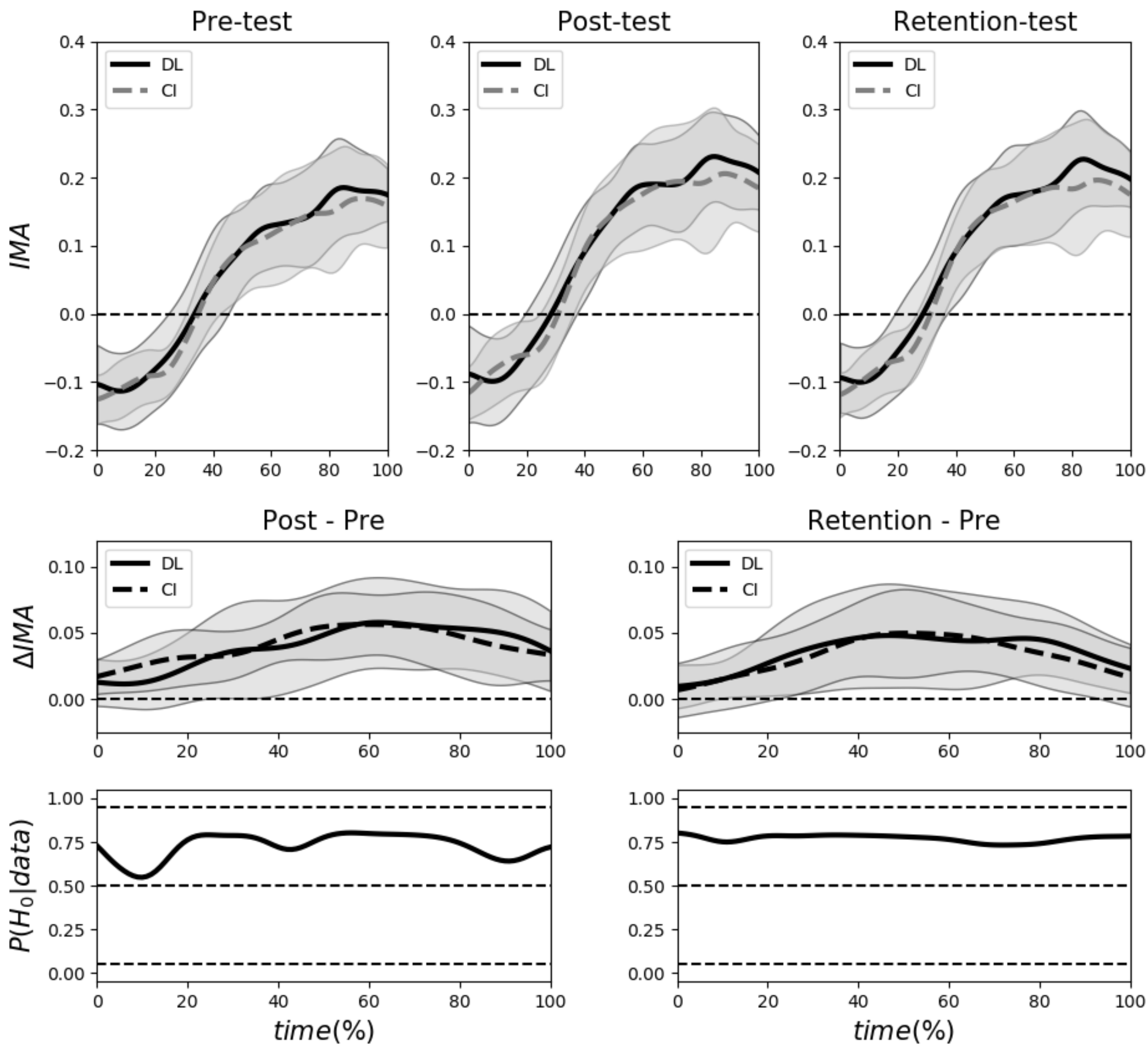


Figure 2: Top panels present IMA time series (mean ± SD cloud) for both groups for target T1 in all three sessions. Positive IMA indicates a movement synergy stabilizing the trajectory of the reaching hand. The middle panels present the changes from baseline (left: ΔIMA_{post} and right: $\Delta IMA_{retention}$). Similar patterns for IMA and ΔIMA were observed for the other analyzed targets (T2, T4, T5, see OSF link). The bottom panels present the Bayesian ANOVA results as a posterior probability map (combining data from all four targets). The trajectory shows the posterior probability of the null hypothesis (H_0, no difference between DL and CI).

DISCUSSION

This study is the first experiment analyzing the effect of DL on a visuomotor response time task, mimicking goalkeeper reaching. response. CI was used as a control method to examine the different prediction of motor learning interference between both paradigms. Both DL and CI introduce variability during practice to accelerate motor learning. The VMRT data were in accordance with the hypothesized interference effect: DL resulted in better learning rates directly after the practice session (negligible improvements in CI), but the difference between both methods was negligible at the retention test. Motion analysis with UCM was done to gain insight into these differences. While we found increased IMA for most subjects, the changes were on average similar between DL and CI.

Visuomotor Response Time. The DL exercises improved VMRT on short term acquisition and retention tests, while the smaller amount of variability from CI was only effective after a rest period where the difference with DL was negligible. However, only a short-term retention test was included and the positive effects of CI may reach full potential only after longer periods (Santos et al., 2014). On average, the higher levels of practice variability from DL thus seem to be effective in reducing the short-term interference effect and to provide continued learning effects during a rest period. The changes in VMRT may indicate changes in visual perception/processing and/or movement speed. As subjects were not constrained to start from a rest position, movement initiation of the hands (or other degrees-of-freedom) could not be determined to distinguish how much each factor contributed to the change in VMRT. We have to stress that the findings pertain to the mean levels and that a large inter-subject variability was seen. Not every subject had shorter VMRT on the post/retention tests, increases up to 50 ms were observed as well in DL. Caballero et al. (2017) reviewed factors that influence the efficiency of practice variability to enhance motor learning. One of their conclusions was that interventions where variability is manipulated per individual subject, based on knowledge of their characteristics, remains a poorly explored area of research. In line with the focus of DL on individual specific optimization (Schöllhorn, 1999), future studies should attempt to find optimal amounts of practice variability based on subject characteristics. Also the practical significance of the results may be questioned as the average reductions in VMRT were relatively low compared to the overall duration of the movement, however, this is likely due to the fact that only a single practice session has been conducted.

Subjective feeling of the learning experience. The question on learning experience through the exercises was included as a qualitative and subjective measure of what is described in the DL literature as stochastic resonance (SR). The rationale is for DL exercises to cover a maximal range of motions patterns to maximize the probability that one of the movement variations resonates with the individual optimum, i.e. that the subject discovers something in the executions that is beneficial for his/her specific constraints at that point in time. However, many variations may have no added value and thus reduce the effective amount of practice. SR is often hauled as the theoretical mechanism behind DL, but has never been tested before (Schölhorn, 2009; Beek, 2011; Serrien et al., 2018; Hossner et al., 2016). While this question definitely does not measure SR, it indicated that subjects in DL were more likely to had a positive learning experience than those in CI. When asked to elaborate, most subjects (also those responding positive in CI) mentioned the exercises where they had to keep moving their hands around. Other exercises were less frequently quoted and were diverse between subjects. Additionally, many subjects in DL spontaneously reported that the exercises were fun to do. This motivational aspect may also have contributed to the difference at the post-test (Wulf & Lewthwaite, 2016).

Index of Motor Abundance. Most subjects started with negative values (random variability in the elemental variables) and showed a small decrease before increasing towards positive values and remaining positive in the second halve of the reaching movement (stabilizing synergy among the elemental variables). The initial random variability can be expected in this task as subjects are not prepared to move in one particular direction when the LED-light targets flash on. Once subjects have decided where to move their hand, a variance stabilizing synergy emerges. While the performance level clearly showed a difference in learning rate between DL and CI, no reason for this difference could be observed at the strength of movement synergies. The IMA was increased in nearly all subjects throughout nearly the entire movement pattern, but this increase was practically similar at post- and retention-test, i.e. no further increase during the rest period. The Bayesian ANOVA model did not reach the pre-set level of 95% posterior probability for the null hypothesis, but it was definitely more likely than the alternative. The difference in practice variability between DL and CI thus did not result in a different strength of movement synergies in this task. The increased IMA may reflect a learning effect irrespective of the type of training (Latash, 2010), but further research will be necessary. It is possible that other behavioural variables could distinguish between DL and CI and future research may attempt to discover these in order to unravel how they cause different performance outcomes.

Limitations of the study and guidelines for future research. The primary limitation of this study is a low level of ecological validity and representative learning design (Pinder et al., 2011), which limits extrapolation to practice in goalkeeping training. In practical settings, avoiding a short-term interference effect is certainly important before a game, but future work is necessary in populations that are specifically involved in goalkeeping to see if they also benefit from these variable training settings and if the effects are reproducible under long-term practice schedules and transferable to real goalkeeping. This experiment was set up to examine short-term acquisition and retention effects and concurrent changes in motor variability (UCM analysis) which required a relatively constrained movement execution. This limited the task to a have only a discrete set of targets at fixed locations. To further improve representative learning design in future applied work with Fitlight™ goalkeeping training, we should try to provide other sources of visual information upon which subjects can react like actions of opponents who are about to throw/kick. The cognitive component of the task can be made more difficult by using unpredictable inter-stimulus intervals (potentially very long to test vigilance), using different colors or noises to cue different tasks, etc.

Adding a control group or a group with repetitive practice (no variability) may help to elucidate whether the observed effect on the post-test was because DL was beneficial or CI was detrimental. Furthermore, when DL and CI training sessions are designed with more specific emphasis on the focus of attention, this would also help to better understand the role of internal (elicited in DL) or external (elicited in CI) focus of attention in the interpretation of results.

The UCM analysis was limited to a 2D geometric model as the primary plane of movement was parallel to the wall. However, a 3D model would be more sensitive and could reveal differences between DL and CI. Also different analyses of the movement patterns could reveal what exactly is being learned at the behavioral level and how this differs between different training paradigms.

CONCLUSION

This was the first study that examines DL and CI on visuomotor response time and motor control in a goalkeeping mimicking task. Immediately after the training session, DL showed stronger improvements in VMRT than CI, but after 1 hour of rest, no differences were seen anymore. Both groups showed improved motor control, as seen by stronger movement synergies after the training, with no difference between DL and CI.

APPENDIX A1: DL and CI training exercises

The DL exercises were selected to let subjects experience many different starting positions, constraints on their degrees-of-freedom, constraints on incoming visual information, additional dual tasks and balance. All subjects received the same order of the exercises but not every subject performed each exercise on every target (random selection of 6 lights per exercise).

DL-exercises:

1. Put both hands on top of each other and move with both hands simultaneous to the target.
1. Stand only on the tip of the toes.
2. Start with the hands as far above the head as possible (return to this position between two lights).
3. Keep both feet as close together as possible.
4. Cover your left eye with your left hand and use only the right hand to hit the targets.
5. Hold your left elbow with your right hand and use only the left hand to hit the targets.
6. Cover your right eye with your right hand and use only the left hand to hit the targets.
7. Stand only on the heel of the feet.
8. Start with both hands on your back (return to this position between two lights).
9. Start with the back against the wall and keep it against the wall during movement, use periferal vision to see the lights flashing on.
10. Move with the dorsal side of the hand to the targets.
11. Keep your elbows straightened all the time (no elbow flexion allowed).
12. Keep your hands into fists all the time.
13. Constantly move your hands around a little on your side (waving, making small circles), holding hands steady is not allowed.
14. Hold your right elbow with your left hand and use only the right hand to move to the targets.
15. Start from a crouched position with the hands on the ground (return to this position between two lights).
16. Stand only on your right foot.
17. Start with both hands on the shoulder (return to this position between two lights).
18. Hold your left hand on your back and use only the right hand.
19. Constantly move your hands around a little in front of you (waving, making small circles), holding hands steady is not allowed.
20. Keep your legs straightened all the time (no knee flexion allowed).
21. Hold your right hand on your back and use only the left hand.
22. Start with the arms straightened in front of the body, pointing to the wall (return to this position between two lights).
23. Stand only on your left foot.
24. First touch the floor with one hand and then move to the target with the other hand.
25. Start with hands behind the head (return to this position between two lights).
26. Keep knees in squat position.
27. Stand with the back to the wall and pivot before moving to the target.
28. Use the left hand for the targets on the right and vice versa.
29. Start with both feet very wide apart (return to this position between two lights).

CI-exercises:

1. Standard motion, no specific instruction. Move as during the test.
2. Put both hands on top of each other and move with both hands simultaneous to the target.
3. Constantly move your hands around a little in front of you (waving, making small circles), holding hands steady is not allowed.

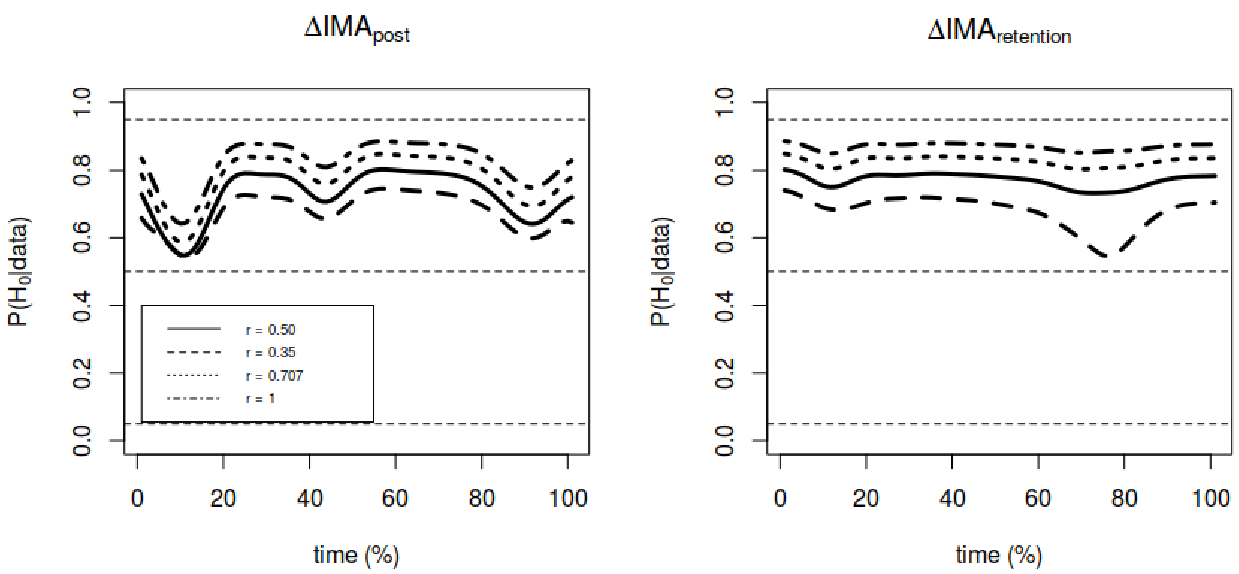
APPENDIX A2: Sensitivity analyses

Table A2.1 presents the Bayes Factors, posterior medians and 95% HDI for a range of prior scale factors for the ANOVAs on ΔVMRT: r = 0.35, 0.50 ('medium' scale, default value used in main manuscript), 0.707 ('wide' scale, √2/2), 1 ('ultrawide' scale). Figure A2 presents the same sensitivity analysis for the ANOVAs on ΔIMA. The scale factor of the random effects (subject ID and target location) was kept fixed at the default 'ultrawide' setting (r = 1), corresponding to an expectation of large inter-individual and target-specific differences. All values for the scale of the priors for the fixed effect of group gave qualitatively similar results as the default setting used in the main manuscript.

Table A2.1: Robustness check of Bayes Factors, posterior medians and 95% HDI for ANOVAs on ΔRT.

	$\Delta VMRT_{post}$		$\Delta VMRT_{retention}$	
	BF_{10}	posterior median [95% HDI]	BF_{01}	posterior median [95% HDI]
r = 0.350	8810	-30.8 [-42.6; -18.5]	2.8	-6.9 [-20.7; 6.3]
r = 0.500	8795	-30.8 [-43.0; -18.6]	2.8	-6.9 [-20.4; 6.5]
r = 0.707	8752	-30.8 [-42.7; -18.5]	2.8	-7.0 [-20.3; 6.7]
r = 1.000	8784	-30.8 [-42.8; -18.4]	2.8	-6.9 [-20.2; 6.5]

Figure A2.1: Posterior probability for H_0 (no difference between DL and CI on ΔIMA). Sensitivity of outcome w.r.t. prior scale factor r.



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